SIMULATION OF AIRCRAFT SORTIE GENERATION UNDER AN AUTONOMIC LOGISTICS SYSTEM

THESIS

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Abstract

Rapidly-changing wartime environments and newly emerging global threats necessitate a highly responsive air power. This responsive air power is directly related to the success of Air Force logistics systems in generating sufficient sorties required for military operations. Briefly, the more efficient the logistic system is, the more powerful the Air Force is.

Parallel to the developments in diagnostic and prognostic technology, autonomic logistics systems (ALS) represent a potential improvement for the aircraft sortie generation process. Currently, Lockheed Martin and the Joint Program Office are developing a new autonomic logistics system for the multibillion F-35 Lightning Joint Strike Fighter project, which is named the "Autonomic Logistics Information System (ALIS).''

Generally, researchers make an analogy between the ALS and the human body's autonomic nervous system since both of them monitor, control, and adjust autonomic responses to external stimuli. Based on this perspective, ALS aims to switch the Air Force logistics mentality from a reactive one into a proactive one to achieve higher sortie generation rates and aircraft availability.

The primary objective of this thesis is to explore the ALS concept in detail and to investigate the F-35's sortie generation process through a discrete-event simulation model developed in Arena® Simulation Software.

To my Father and Mother

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Table of Contents

Page

Abstract iv

Acknowledgments vi

Table of Contents vii

List of Figures x

List of Tables xii

List of Equations xv

I. Introduction 1

Background 2
Autonomic Logistics (AL) Concept 2
Sortie Generation Process 3
Previous Work 7
Problem Statement 7
Purpose Statement 8
Research Objectives and Questions 8
Scope and Assumptions 9
Summary 9

II. Literature Review 10

Introduction 10
Sortie Generation Process 10
The F-35 Project 13
Autonomic Logistics (AL) Concept 16
Autonomic Logistics Information System (ALIS) 18
Maintenance Concepts and ALIS 21
Maintenance Process within Legacy Logistics System 22
Maintenance Process within ALIS 23
Action Request (AR) System within ALIS 24
Prognostic Health Management (PHM) within ALIS 26
Learning Curves and Reliability Growth 28
Conclusion 32

III. Methodology 33

Chapter Overview 33

Simulation in Arena 33
Assumptions 33
Data Collection 35
Model Development 37
Model Initialization *39*
Preflight Operations *40*
Sortie *41*
Post-Flight Operations *42*
PHM Area *42*
Troubleshooting and Action Request *44*
Maintenance Operations *46*
Implementation of the Reliability Growth for the MFHBCF 48
Implementation of the Learning Curves 50
Model Verification and Validation 52
Conclusion 53

IV. Analysis and Results 55

Measures of Performance (MOP) for the Sortie Generation Process 55
Run Length and Replication 56
Design of Experiment 57
Output Analysis 59
Tests of the ANOVA Assumptions *59*
ANOVA Analysis for AA Rate *60*
ANOVA Analysis for FSE Rate *63*
Analysis of the PHM Level *67*
Conclusion 71

V. Conclusions and Recommendations 73

Introduction 73
Research Summary 73
Research Conclusion 74
Recommendations for Further Study 75

Appendix A: Normality Test Results 77

Appendix B: Tests of the ANOVA Assumptions 78

Appendix C: Tukey Test Results for AA Rate 80

Appendix D: Tukey Test Results for FSE Rate 84

Appendix E: ANOVA Results for MFHBFA 88

Appendix F: ANOVA Results for FCR 89

Appendix G: ANOVA Results for CFDR 90

Appendix H: ANOVA Results for FIR..91

Appendix I: ANOVA Results for KFAR..92

Bibliography 93

List of Figures

Page

Figure 1. Sortie Generation Process (Partially adapted from (Faas, 2003)) 4

Figure 2. The Flow of Unscheduled and Scheduled Maintenance (Adapted from Faas, 2003) 6

Figure 3. F-35 Aircraft Vision (McCollom, 2011) 15

Figure 4. ALIS Issue-Resolution Process (Government Accountability Office, 2014) ... 25

Figure 5. Learning Curve 28

Figure 6. Sortie Generation Model 39

Figure 7. Model Initialization Process 40

Figure 8. Pre-flight Operations 40

Figure 9. Sortie Process 41

Figure 10. PHM Area 42

Figure 11. Troubleshooting Process 45

Figure 12. Action Request Process 46

Figure 13. Maintenance Processes 47

Figure 14. LS Means Plots of the Factors 61

Figure 15. LS Means Plot of the PHM -RG Rate Interaction 62

Figure 16. LS Means Plot of the PHM -LC Rate Interaction 62

Figure 17. LS Means Plot of the RG Rate-LC Rate Interaction 62

Figure 18. AA Rates under Different Factor Combinations 63

Figure 19. LS Means Plots of the Factors 65

Figure 20. LS Means Plot of the PHM Level-RG Rate Interaction 65

Figure 21. LS Means Plot of the PHM Level-LC Rate Interaction 66

Figure 22. LS Means Plot of the RG Rate-LC Rate Interaction 66

Figure 23. FSE Rates under Different Factor Combinations... 67

Figure 24. Total Maintenance Time vs. MFHBFA.. 68

Figure 25. Impact of MFHBFA on the FSE Rate and AA Rate 69

Figure 26. Impact of FCR on the FSE Rate and AA Rate 70

Figure 27. Impact of CFDR on the FSE Rate and AA Rate 70

Figure 28. Impact of FIR on the FSE Rate and AA Rate 71

Figure 29. Impact of KFAR on the FSE Rate and AA Rate 71

Figure 30. Shapiro-Wilk Test Results for the Residuals of FSE Rate 77

Figure 31. Shapiro-Wilk Test Results for the Residuals of AA Rate 77

Figure 32. Shapiro-Wilk Test Results for FSE Rate (Normality).................................... 78

Figure 33. Shapiro-Wilk Test Results for AA rate (Normality) 78

Figure 34. Residual Plot of the FSE Rate (Constant Variance)....................................... 78

Figure 35. Residual Plot of the AA Rate (Constant Variance).. 79

Figure 36. Overlay Plot of the FSE Rate’s Residuals (Independence)............................ 79

Figure 37. Overlay Plot of the AA Rate’s Residuals (Independence).............................. 79

List of Tables

Page

Table 1. Timeline of Major Events in the F-35 Program (Government Accountability Office, 2014) 14

Table 2. Primary ALIS Applications and the F-35 Program Office's Assessment of Their Functionality Status as of January (Government Accountability Office, 2016) 20

Table 3. Autonomic Logistics and Information System Costs (Government Accountability Office, 2016) 21

Table 4. Maintenance Concepts (Vandawaker, 2015) 22

Table 5. Metrics of F-35's Diagnostic Capabilities 27

Table 6. Examples of Learning Curves Effects (Cunningham, 1980) 29

Table 7. Grow Rates for Several Historical Aircraft (The Office of The Director, 2015) 30

Table 8. Process Times and Related Distributions 36

Table 9. Actual MFHBCF, MCMTCF, MFHBFA and PHM Data for F-35A (The Office of The Director, 2015) 37

Table 10. Process Times within the AR System 37

Table 11. Global Variables 38

Table 12. Cumulative Flight Hours versus MFHBCF 48

Table 13. Reliability Growth for MFHBCF 50

Table 14. Impact of a 95% Learning Rate on the Resolution Time 51

Table 15. Impact of the 95% Learning Rate on the MCMTCF 52

Table 16. Real World FSE Rate versus Simulation FSE Rate 53

Table 17. Critical Factors and Their Associated Levels 57

Table 18. Design of Experiment 58

Table 19. ANOVA Results for the AA Rate 60

Table 20. Effect Tests for AA Rate 61

Table 21. ANOVA Results for the FSE Rate 64

Table 22. Effect Tests for FSE Rate 64

Table 23. Tukey Tests for PHM Level, RG Rate, and LC Rate 80

Table 24. Tukey Test for Two-way Interactions of PHM Level and RG Rate 81

Table 25. Tukey Test for Two-way Interactions of PHM Level and LC Rate 82

Table 26. Tukey Test for Two-way Interactions of RG Rate and LC Rate 83

Table 27. Tukey Tests for PHM Level, RG Rate, and LC Rate 84

Table 28. Tukey Test for Two-way Interactions of PHM Level and RG Rate 85

Table 29. Tukey Test for Two-way Interactions of PHM Level and LC Rate 86

Table 30. Tukey Test for Two-way Interactions of RG Rate and LC Rate 87

Table 31. ANOVA of the MFHBFA vs. Maintenance Time 88

Table 32. ANOVA of the MFHBFA vs. AA Rate 88

Table 33. ANOVA of the MFHBFA vs. FSE Rate 88

Table 34. ANOVA of the FCR vs. FSE Rate 89

Table 35. ANOVA of the FCR vs. AA Rate 89

Table 36. ANOVA of the CFDR vs. FSE Rate 90

Table 37. ANOVA of the CFDR vs. AA Rate 90

Table 38. ANOVA of the FIR vs. FSE Rate 91

Table 39. ANOVA of the FIR vs. AA Rate 91

Table 40. ANOVA of the KFAR vs. FSE Rate 92

Table 41. ANOVA of the KFAR vs. AA Rate 92

List of Equations

Page
Equation 1 29

Equation 2 31

Equation 3 31

SIMULATION OF AIRCRAFT SORTIE GENERATION UNDER AN AUTONOMIC LOGISTICS SYSTEM

I. Introduction

Currently, Turkey has the second greatest armed forces in NATO, and the Turkish Air Force (TURAF) is the most deterrent and destructive element of this large force. TURAF defines its vision as;

> To become an aviation and aerospace power competing with the age, which keeps basic values of the Turkish Air Force alive, trains highly-educated aviator manpower, adopts a contemporary management approach**, possesses high technology and utilizes it efficiently**, ensures deterrence against all kinds of threats in its region, is capable of conducting uninterrupted separate/joint/combined operations anywhere required by national interests and strengthens its superiority through national defense industry (Turkish Air Force, 2016).

TURAF has gone through many transitions since its foundation in 1911 to fulfill its goal of possessing high technology and utilizing it efficiently. In particular, the acquisition of F-16 Fighting Falcon Combat Aircraft in 1987 is assumed to be the most remarkable of those transitions.

On July 11, 2002, when Turkey decided to join as the seventh international partner in the F-35 Project, another important technology transition process was initiated for TURAF. Presently, Turkey is planning to procure 100 F-35s, and the first delivery (two aircraft) will be made in 2018 (Undersecretariat of Defense Industries, 2016).

The F-35's unsurpassed technological systems and unique stealth capabilities ensure that it will be the future of Turkish national security for decades to come. It will both introduce a new operational concept and lead a logistics innovation. Its cutting edge Autonomic Logistics System will switch TURAF's logistics mentality from a reactive

one into a proactive one, which will enable higher sortie generation rates and aircraft availability in a more cost-efficient manner.

This thesis develops a discrete-event simulation model of the F-35's sortie generation process to provide decision makers with a better understanding of the Autonomic Logistics concept and its impact on the logistics and operational side by enabling "what-if" analysis.

Background

Rapidly-changing wartime environments and newly emerging global threats necessitate highly responsive air power using cutting-edge war technology. Parallel to this need, the F-35 project emerged in late 1995. According to the US Government Accountability Office, the F-35 is the most ambitious and expensive weapon system in DOD's history, with $400 billion acquisition cost and $891 billion sustainment cost over its planned 56-year life cycle (Government Accountability Office, 2016).

Responsiveness of an air power is directly related to the success of its logistics system in generating sufficient sorties required for military operations. The F-35 program developers recognized the Autonomic Logistics concept as the key element to a more efficient and proactive logistics system to make the F-35 a highly lethal, affordable, supportable, and survivable aircraft.

Autonomic Logistics (AL) Concept

The term "Autonomic Logistics" (AL) was coined to describe an essentially automatic set of processes to ensure maximum sortie generation with minimum logistics footprint and costs, while still maintaining high mission reliability (Henley, Currer,

Scheuren, Hess, & Goodman, 2000). It is an inevitable result of the high-technology diagnostic and prognostic applications in the field of equipment support. In particular, the successful implementation of an AL System in the F-35 fighter, Autonomic Logistics Information System (ALIS), marked the formation of AL mode. The AL system works much the same way as a human body's autonomic nervous system. It monitors, controls, and adjusts autonomic responses to external stimuli.

According to the AL concept, the signals coming from special sensors embedded on aircraft are examined and analyzed constantly for the entire sortie generation process, and fault detection, fault isolation, fault prediction and reporting are made automatically by the aircraft Prognostic and Health Management (PHM) system. The logistics personnel from maintenance to supply are informed about the health status of the aircraft all the time. Therefore, when the aircraft lands, the right personnel, equipment, and material are at the right place at the right time, and performance parameters presumably improve significantly.

Sortie Generation Process

The main purpose of the AL concept is to improve the aircraft sortie generation process. Sortie generation is a cyclic process of flight related activities and has been the same for many years (Faas, 2003). The aim of this process is to achieve a certain sortie generation rate (SGR), which is the number of flight missions carried out within a specific timeframe. SGR is a key factor of a military aircraft's combat effectiveness and also seen as an important metric for senior commanders to evaluate readiness of an air force to apply airpower (Guoqing, Hongzhao, & Yuanhui, 2010).

Literature reviews indicate that there is not a unanimous approach regarding the starting point of the sortie generation cycle or the steps within the cycle. However, it is widely accepted that sortie generation is a combination of inspection, service, flight, and maintenance operations (Aykiri, 2016; Faas, 2003; Guoqing et al., 2010; Rebulanan, 2000; Rossetti & McGee, 2006). In this thesis, sortie generation activities are gathered under four groups as pre-flight operations, sortie, post-flight operations, and maintenance operations. Pre-flight operations are assumed as the first stage of the sortie generation process. Figure 1 represents the entire sortie generation process with a different colored background for each main group.

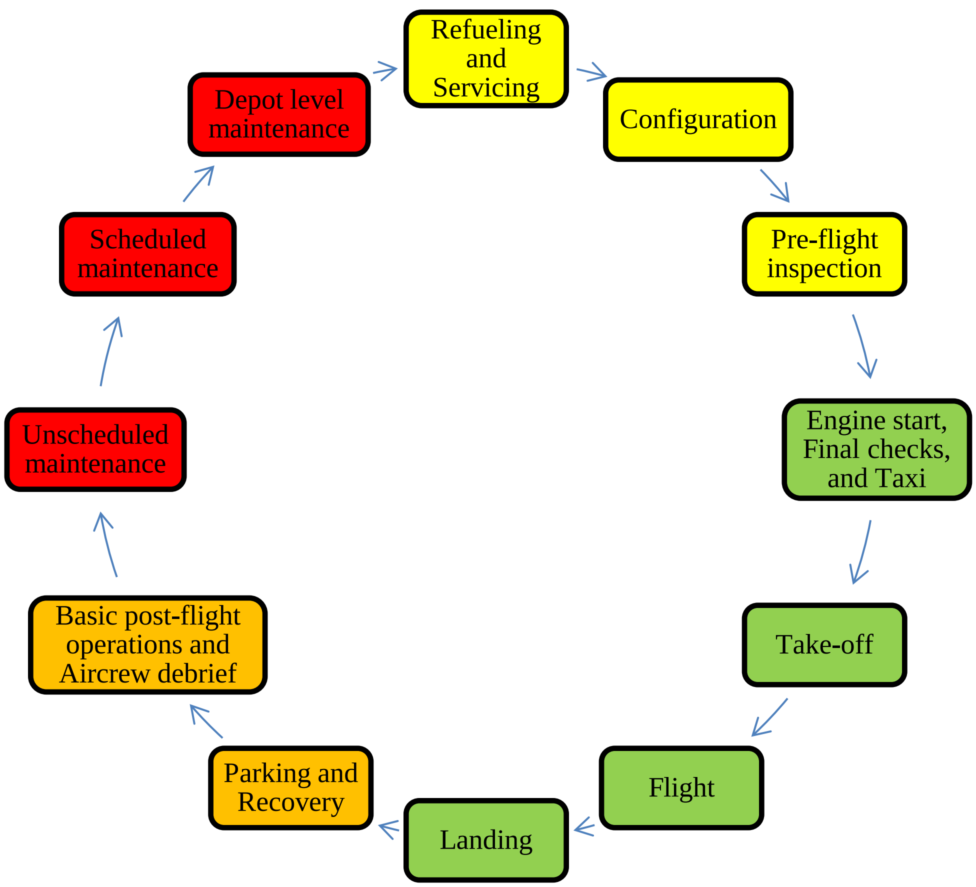


Figure 1. Sortie Generation Process (Partially adapted from (Faas, 2003))

- **Pre-flight operations:** When a flight mission is planned, the aircraft is refueled and some servicing (oil, tire, fluid check etc.) is applied if needed. Then, mission specified weapons and pods are installed onto the aircraft. Since pre-flight operations are standardized actions, their completion times do not vary significantly from their average.
- **Sortie:** Following the pre-flight inspection the engine is started and the aircraft begins taxiing onto the runway. Then it takes off, executes the planned mission, and comes back for landing. A sortie's duration depends on the type of the mission. For the same mission type, usually it does not vary from its average. Expert views and literature reviews indicate that most of the component failures occur in this phase.
- **Post-flight operations:** Following the landing, the aircraft is moved to the parking location and munitions are downloaded. While the aircrew conducts their debriefing to the maintenance crew, concurrently some basic post-flight operations (BPO) are applied to check the aircraft health status. If there is no fault found during the BPO, the aircraft is routed to the aircraft pool for the next mission. If any fault is found, an appropriate maintenance process is initiated to fix the problem.
- **Maintenance operations:** There are three types of maintenance applied to the aircraft: 1) Unscheduled maintenance; 2) Scheduled maintenance; 3) Depot level maintenance. Unscheduled maintenance is conducted to fix the unexpected failures occurring in any step of the sortie generation process. Scheduled maintenance (preventive maintenance) is applied to change the time-sensitive

components which reach a predetermined flight hour-limit, no matter if there is a malfunction or not. While unscheduled maintenance may last for several hours, scheduled maintenance can take a couple of days. Depot level maintenance is also executed based on the accumulated flight hours. Some modifications programs are applied to bring the currently fielded aircraft to their expected airframe structural lifespan and usually require several months (The Office of The Director, 2015). Figure 2 briefly represents the maintenance process flow.

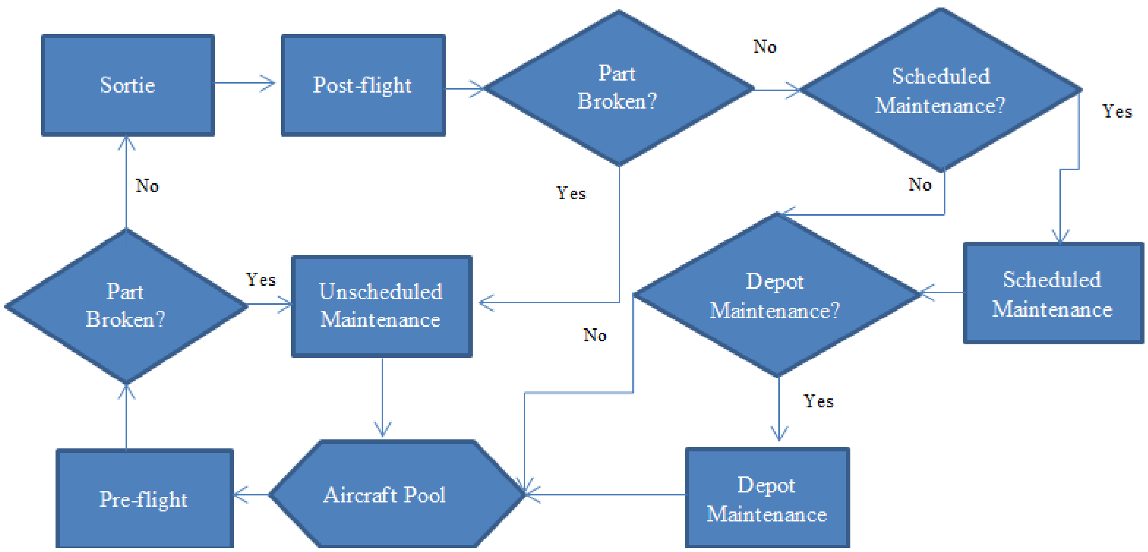


Figure 2. The Flow of Unscheduled and Scheduled Maintenance (Adapted from Faas, 2003)

Literature reviews indicates that an ALS is expected to make the most significant contribution to the maintenance operations by introducing a proactive approach over the reactive approach used today. Therefore, the main focus of our simulation model is the maintenance processes portion of the sortie generation cycle, with particular emphasis on unscheduled maintenance. Impacts of ALS on maintenance operations are explained in detail in the following chapters.

Previous Work

Due to its great value to a military force in terms of cost, sortie generation, and aircraft availability, the Autonomic Logistics System (ALS) has become a popular subject of scientific research. An increasing number of simulations and analytical studies are being conducted to analyze the AL in depth. Literature reviews showed that some pioneering simulation studies regarding the ALS and sortie generation process were conducted by former AFIT students.

While Rebulanan (2000) and Malley (2001) used an object-oriented design with JAVA® and Silk® programming languages, Yager (2003) built a closed queuing model and Faas (2003) developed a discrete event simulation model with Arena® software to investigate the possible impacts of the ALS on the sortie generation process.

These studies were conducted in the early 2000s, a time when the F-35 project and ALS were in their infancy, and mainly investigated ALS from a conceptual perspective. Researchers were unable to use real F-35 data due to the fact that a working system didn't exist, and none of them included Learning Curves (LCs) and reliability growth concepts. Therefore, this research attempts to fill that gap in the scientific field by building a simulation model based as much as possible on actual F-35 data. Moreover, LCs and reliability growth are included into the model logic to obtain more realistic outputs.

Problem Statement

Although F-35 aircraft will be the main TURAF combat element in the near future, its logistics properties and capabilities are not well known. Decision makers and

planners within the TURAF need to recognize and appreciate the potential impacts of the AL concept to manage F-35 fleet more effectively and efficiently.

Purpose Statement

In this study, the ALS is investigated in detail and a discrete-event simulation model for the F-35 sortie generation process is developed using Arena® Simulation Software. After collecting the data from the simulation model, statistical analyses are performed through JMP® Software in designed experiments to determine the ALS's impacts on the measures of performance (MOPs) of the F-35's sortie generation process.

Research Objectives and Questions

The Sortie generation process includes many parameters, which makes it extremely difficult to exhaustively analyze. Therefore, the main objective of this research is to provide a useful simulation model for decision makers to recognize the key factors within the ALS and their potential impacts on MOPs of the F-35's sortie generation process. The following questions capture the main focus of our research:

1. What impact does the maturity level of the PHM system have on the MOPs of the F-35's sortie generation process?

2. What impact do learning curves have on the MOPs of the F-35's sortie generation process?

3. What impact does reliability growth have on the MOPs of the F-35's sortie generation process?

Scope and Assumptions

Presently, there are three variants of the F-35. This research specifically investigates the sortie generation process of the conventional F-35 variant, the F-35A, since it is the only variant that will be procured by Turkey.

Additionally, the F-35 aircraft is a very complex system consisting of many subsystems, and its availability is directly dependent on the functionality of all those subsystems. However, modelling a sortie generation process with all those subsystems would be too complicated and time consuming, since each of them might have different failure rates and repair times. Therefore, for simplicity, the scope of this research is limited to only mission critical failures encountered by the F-35A variant. No LRC (Line Replaceable Component) specification is made and all LRCs are assumed to have similar failure rates and repair times. Moreover, only diagnostic capability of the F-35 is modeled, since prognostic capability is not yet functional.

Summary

This chapter described the rationale behind the research with regards to the F-35 project, Autonomic Logistics, and aircraft sortie generation, and provided an overview of the problem statement, purpose statement, research objective, research questions, scope, and assumptions. Chapter II presents reviews of the existing literature on the sortie generation process. Chapter III describes the data used to meet the research objectives, as well as the data analysis and model development. Chapter IV provides results of the research, while Chapter V provides conclusions and recommendations for further research.

II. Literature Review

Introduction

This chapter examines prior researches conducted in the area of the sortie generation process, Autonomic Logistics, and Learning Curves. Also, the F-35 project is discussed from a logistics basis. Furthermore, the present situation of the F-35's Autonomic Logistics Information System is put forward in the view of official reports presented by the United States Government Accountability Office (GAO).

Sortie Generation Process

As described in Chapter 1, sortie generation is a combination of many activities dedicated to produce desired number of sorties within a limited time period. Due to its paramount importance for an air force's combat effectiveness and deterrence, sortie generation has been a popular subject of scientific research for many years. Some key studies conducted in this field are presented below.

Guoqing et al. (2010) developed an approximate analytical method producing highly similar results to those obtained from long simulations. Their study showed that sortie generation rate was the key parameter for a military aircraft's combat effectiveness.

MacKenzie et al. (2012) also examined the relationship between the number of sorties flown and Combat Mission Readiness (CMR). They assumed CMR was a key metric for senior commanders to evaluate readiness of an air force to apply air power. They demonstrated that different mixes of maintenance personnel skill levels significantly affect the sortie generation rate.

Iwata and Mavris (2013) focused on supply activities within the sortie generation process. They put forward the relationship between mission capable (MC) rate and average part delivery time by conducting a case study using a Python simulation tool. They showed that MC rate began to decrease after the delivery time grew beyond 1.0 day, and flattened off at a MC rate of 0.7 from 1.4 to 1.9 days. After that point, MC rate fell rapidly.

Harris (2002) noted that the Logistics Composite Model (LCOM), currently being used by USAF to calculate sortie rates, requires a great amount of input data and processing time. Therefore, LCOM hinders the commander's flexibility, responsiveness, and ability to create alternative options. Thus, he proposed the Sortie Generation Rate (SGR) model which was a generic sortie model with simple operational input and quick turnaround. The SGR model generated sortie rates that were close to the actual sortie rates.

Lastly, Manuel D. Rossetti and Joshua B. McGee (2006) demonstrated that simulation could provide valuable information for decision-making at the unit level and provide much needed assistance in the generation and execution of a weekly flying schedule. Thus, their model allowed the unit level logistics planners to compare alternative schedules and perform what-if analysis.

Literature reviews show that the impacts of the Autonomic Logistics (AL) on sortie generation process became another focus topic for researchers when the F-35 project was introduced in mid-1990. Some pioneering simulation studies in this area were conducted by AFIT graduates.

First, Rebulanan (2000) created a computer simulation model of the ALS, called ALSim, using object-oriented design with Java and Silk programming languages to compare the ALS with the existing logistics system. His study indicated that the ALS could improve the system performance in terms of aircraft availability, sortie generation rate, and time waiting for parts. Following Rebulanan's study, Malley (2001) added the reality of false alarms into Rebulanan's ALSim to generate more realistic failure detection times in order to make the simulation more useful for decision making.

Next, Faas (2003) built a discrete event simulation model of sortie generation with Arena® software to investigate the ALS concept. His model also indicated that the ALS equipped aircraft could perform more effectively than a non-ALS aircraft up to a point. In the best case scenario, in which false alarms were at a minimum level, there was an 8% improvement in Mission Capable rate. At the other factor-level combinations, the ALS performed marginally better or even worse than the non-ALS aircraft.

Cassady et al. (2006) developed a simulation model with Arena to explore the impacts of diagnostic and prognostic errors on fleet performance and compare prognostic to scheduled maintenance. Focusing on type-1 and type-2 errors, they showed that prognostics could be an effective tool in some cases (even in the presence of significant prognostic errors) and a very ineffective tool in other cases. In some cases, prognostic errors could make a situation worse than a "run to failure" policy (unscheduled maintenance) would do.

To sum up, the literature reviews demonstrated that simulation is a useful tool to investigate aircraft sortie generation processes. Moreover, sortie generation rate and aircraft availability are the two most commonly used sortie generation performance

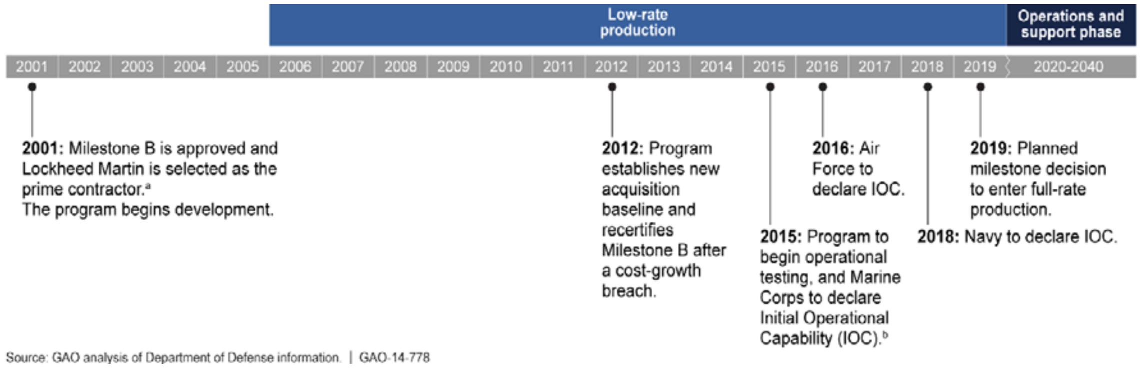
parameters. However, none of the studies used real-world F-35 data. They mostly investigated sortie generation from a theoretical basis. Therefore, developing a simulation model based on real-world F-35 data may provide significant contributions to this research area.

The F-35 Project

The second topic investigated through the literature reviews was the F-35 project. According to the GAO reports, the F-35 is the most ambitious and expensive weapon system in DOD's history with sustainment costs comprising the vast majority of DOD's $1.3 trillion cost estimate. It is a joint, multinational acquisition intended to develop and field a family of next-generation strike fighter aircraft for the United States Air Force, Navy, and Marine Corps, and eight international partners (United Kingdom, Italy, the Netherlands, Turkey, Canada, Australia, Denmark, and Norway). Lockheed Martin is the primary aircraft contractor and Pratt & Whitney is the engine contractor (Government Accountability Office, 2016).

The F-35 project is currently in the low-rate production stage with full-rate production planned to start by 2019. The timeline of major events in the F-35 program is presented in Table 1.

Table 1. Timeline of Major Events in the F-35 Program (Government Accountability Office, 2014)



According to the DOD, there will be three variants of the F-35:

- **The conventional takeoff and landing (CTOL) variant,** designated the F-35A, is a multirole, stealthy strike aircraft replacement for the Air Force's F-16 Falcon and the A-10 Thunderbolt II aircraft, and complements the F-22A Raptor. Turkey will procure the CTOL variant.
- **The short takeoff and vertical landing (STOVL) variant,** designated the F-35B, is a multirole, stealthy strike fighter that replaces the Marine Corps' F/A-18C/D Hornet and AV-8B Harrier aircraft.
- **The carrier-suitable variant (CV),** designated the F-35C provides the Navy a multirole, stealthy strike aircraft to complement the F/A-18.

McCollom and Worth (2011) state that the F-35 aircraft vision rests on four main pillars: Affordability, Lethality, Supportability, and Survivability (see Figure 3). The program has a unique commitment to the creation of a new form of aircraft and operational systems, with a fundamental and essential focus on two of the four program ‘‘pillars’’- Supportability and Affordability.

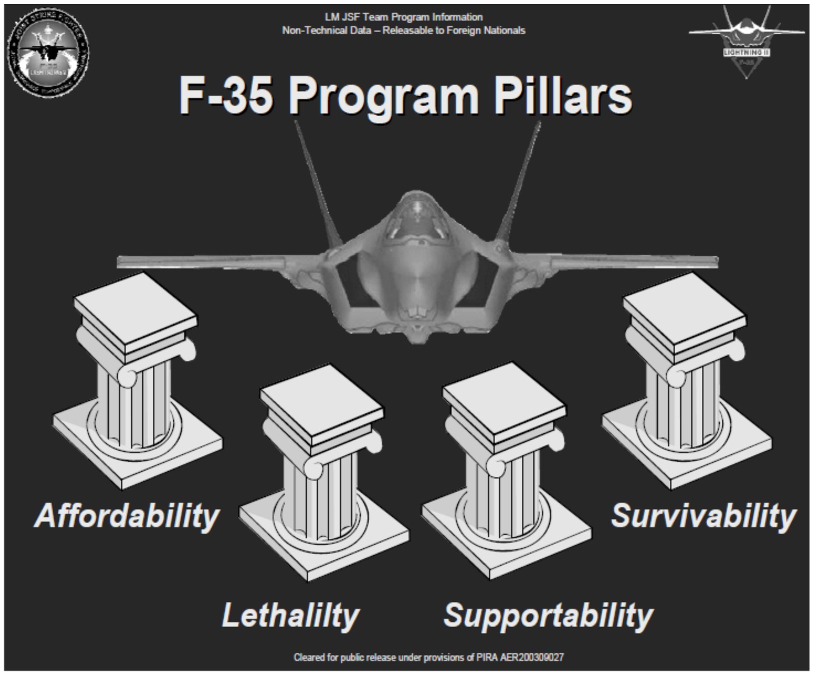


Figure 3. F-35 Aircraft Vision (McCollom, 2011)

The supportability and affordability of the F-35 are directly related to the sustainment costs, since they are the most significant cost driver of the F-35 program. The sustainment costs consist of Operation and Support (O&S) costs incurred from the initial system deployment through the end of system operations, and include all costs of operating, maintaining, and supporting the fielded system. The F-35 program office develops an annual estimate for the O&S costs of maintaining and supporting the F-35 for 56 years. In its most recent estimate (2014), the program office estimates cost at about $891 billion to sustain the entire F-35 fleet over its life cycle (Government Accountability Office, 2016).

These financial estimates related to the F-35's sustainment highlight the importance of a new logistics system that should be far more efficient than the legacy

logistics systems. The F-35 program developers recognize the Autonomic Logistics concept as the key element to a more efficient logistics system which will make the F-35 a highly lethal and affordable aircraft.

Autonomic Logistics (AL) Concept

The AL concept is the inevitable result of high-tech diagnostic and prognostic advances in the field of equipment support. It aims to achieve condition-based maintenance by using the health status data coming from special sensors embedded onto the aircraft.

The AL concept has four major parts: 1) Prognostics and Health Management (PHM); 2) Joint Distributed Information System (JDIS); 3) Technology-enabled maintainer; 4) Responsive logistics infrastructure (Henley et al., 2000).

PHM is a kind of on-board artificial autonomic nervous system which is vital for AL operations. Through the use of intelligent reasoners, PHM detects, isolates, and predicts failures or triggers a single maintenance action in the event of unpredicted failure (Henley et al., 2000). Henley et al. defined key benefits of PHM as:

- Improved safety,
- Improved sortie generation,
- Triggering of AL functions,
- Reduced life cycle costs,
- Reduced logistics footprint,
- Triggering of system reconfiguration to achieve mission reliability,

- Providing advanced onboard diagnostics and testability to reduce the skillset needed by maintainers.

JDIS is an advanced information technology providing decision support tools and an effective communication network linking aircraft with the logistics infrastructure to provide proactive support and enable remote maintenance when needed. The information fusion capability of the PHM system allows JDIS to output and pass on actions and recommendations rather than just data (Hess, Calvello, & Dabney, 2004). By fusing the information coming from sensors, it produces the following outputs:

- Maintenance Information/knowledge,
- Supply chain management information,
- Health and usage information,
- Forecast aircraft availability data,
- Best use of resource recommendations,
- Training Management (Henley et al., 2000).

With the help of the outputs above, the following tasks are automatically performed through JDIS: Mission planning, maintenance action scheduling, ordering of spare parts, scheduling of flight and maintenance training, assignment of specific pilots to specific missions based upon experience and readiness, assigning specific aircraft to specific missions based upon aircraft availability and capability, and storing maintenance, training, spare part, and logistic information in the data warehouse (Hess et al., 2004).

The maintainer in the AL concept is enabled with a full set of technological tools to prepare the aircraft for its next sortie in the most effective way. The maintainer's toolset consists of:

- Comprehensive knowledge of the actual aircraft health before beginning work,
- Appropriate and timely training to conduct the task,
- All the necessary material on hand before commencement of work,
- Interactive guidance available in real time to provide supplementary information as required (Henley et al., 2000).

A technologically enabled maintainer is capable of efficiently and effectively maintaining the F-35 with less specialized training and more "on the spot" training. This allows the use of fewer maintainers, cross trained over many sub-systems (Hess et al., 2004).

Finally, a flexible and responsive logistics infrastructure is needed to get full benefit from the substantial PHM capability, technologically enabled maintainer, and highly capable JDIS.

Autonomic Logistics Information System (ALIS)

The F-35 program developers recognize the AL concept as the key enabler to a highly supportable and affordable fighter. The AL implementation in the F-35 fighter aircraft is named the "Autonomic Logistics Information System'' (ALIS), which was also called the Joint Distributed Information System (JDIS) by many previous researchers. ALIS is one of three major components that make up the F-35 air system, along with the aircraft and the engine, and comprises both hardware and software (Government Accountability Office, 2014).

Lockheed Martin, the prime contractor of the F-35 project, describes ALIS in its official website as: "ALIS serves as the information infrastructure for the F-35,

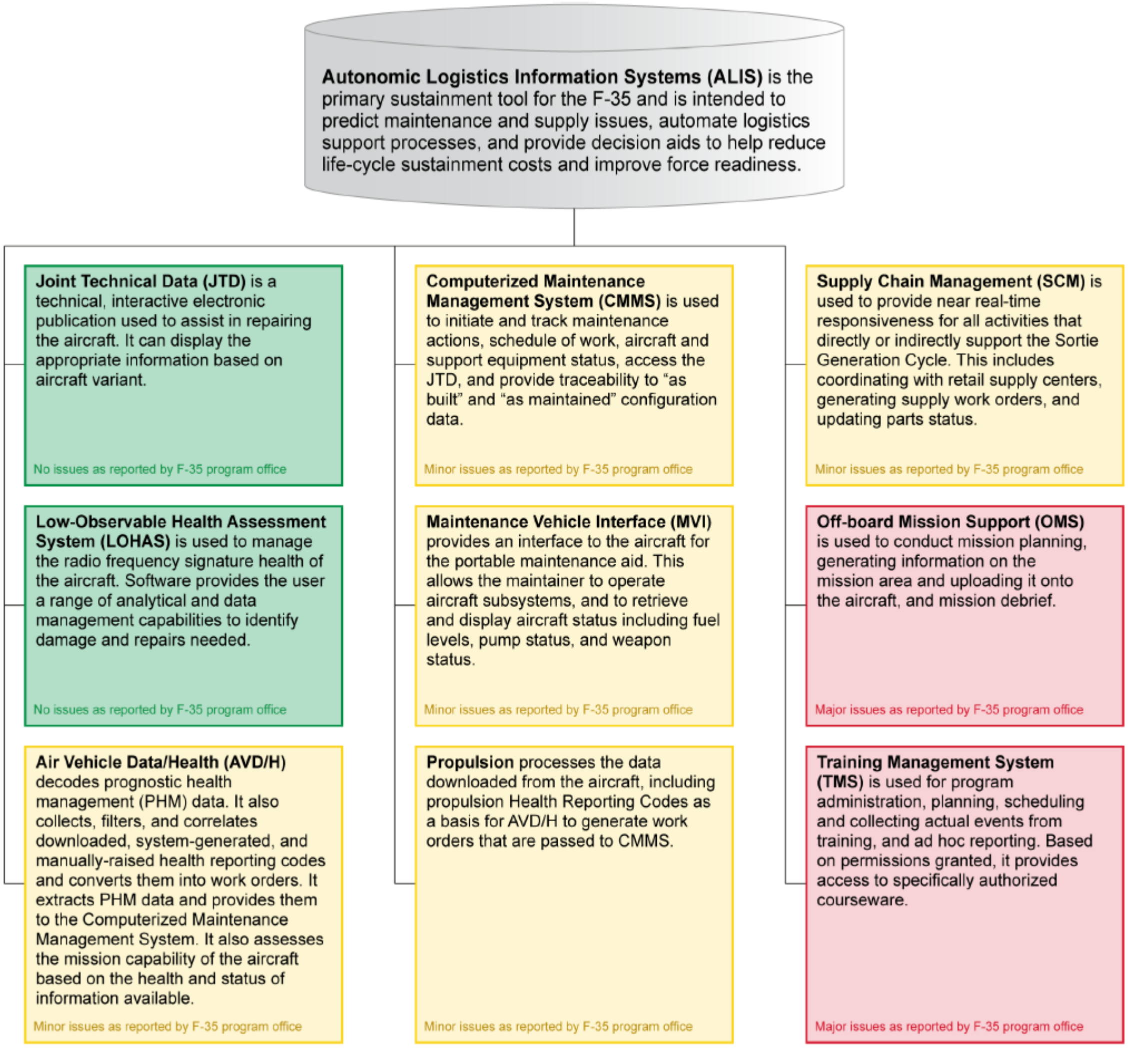
transmitting aircraft health and maintenance action information to the appropriate users on a globally-distributed network to technicians worldwide. ALIS receives Health Reporting Codes via a radio frequency downlink while the F-35 is still in flight; this enables the pre-positioning of parts and qualified maintainers so that when the aircraft lands, downtime is minimized and efficiency is increased." (Lockheed Martin, 2016).

ALIS has three main hardware components:

- **The Autonomic Logistics Operating Unit (ALOU):** The ALOU is the computer server that all F-35 data ultimately are sent through and it supports communications with and between the government and the contractor's systems.
- **The Central Point of Entry (CPE):** The CPE is configured to provide software and data distribution for the entire F-35 fleet in the United States, enables interoperability with national (government) systems at the country level, and enables ALIS data connectivity between bases. Each international partner operating F-35 aircraft is expected to have its own CPE at other locations.
- **The Standard Operating Unit (SOU):** SOUs provide all ALIS capabilities to support flying, maintenance, and training. They also provide access to applications to operate and sustain the aircraft (Government Accountability Office, 2016).

General architecture and primary applications of the ALIS are presented in Table 2. According to F-35 Program Office's assessment of functionality status as of January 2016, green applications (JTD, LOHAS) have no issues, yellow applications (AVD/H, CMMS, MVI, Propulsion, SCM) have minor issues, and red applications (OMS, TMS) have major issues.

Table 2. Primary ALIS Applications and the F-35 Program Office's Assessment of Their Functionality Status as of January (Government Accountability Office, 2016)



Source: GAO presentation of Department of Defense analysis. | GAO-16-439

DOD has estimated ALIS related total costs to be about $16.7 billion over the F-35's 56-year life cycle. However, a 2013 DOD commissioned plan found that schedule slippage and functionality problems with ALIS could lead to $20-100 billion in additional costs.

Table 3. Autonomic Logistics and Information System Costs (Government Accountability Office, 2016)

Cost element	Then-year dollars in millions
Development costs	
Expended as of December 2015	505
Estimated development costs remaining through 2017	57
Subtotal	**$562**
Estimated procurement costs	
Hardware	931
Spare parts	147
Subtotal	**$1,078**
Estimated sustainment costs	
Contractor support[a]	8,050
Technology refresh[b]	3,850
Hardware maintenance agreements	1,603
Software licensing agreements	1,598
Subtotal	**$15,101**
Total	**$16,741**

Source: GAO analysis of F-35 program office data. | GAO-16-439

Maintenance Concepts and ALIS

Faas (2003) defines maintenance as the heart of flight line operations due to its paramount importance in generating a desired number of sorties. It is one of the most significant cost drivers in aircraft sustainment. According to the DOD, maintenance costs hold almost 30 percent of the F-35's sustainment costs (Government Accountability Office, 2014).

Aircraft maintenance has evolved over time from a "fix it when it breaks" policy to a condition-based maintenance concept (Vandawaker, 2015). Table 4 presents a categorical breakdown of maintenance approaches and their attributes.

Table 4. Maintenance Concepts (Vandawaker, 2015)

Maintenance Approaches				
Category	Reactive	Proactive		
Sub-Category	Run-to-fail	Preventive	Predictive	
	Fix when it breaks	Scheduled maintenance	Condition-based maintenance-diagnostic	Condition-based maintenance-prognostic
When Scheduled	No scheduled maintenance	Maintenance based on a fixed time schedule for inspect, repair and overhaul	Maintenance based on current condition	Maintenance based on forecast of remaining equipment life
Why Scheduled	N/A	Intolerable failure effect and it is possible to prevent the failure effect through a scheduled overhaul or replacement	Maintenance scheduled based on evidence of need	Maintenance need is projected as probable within mission time
How Scheduled	N/A	Based on the useful life of the component forecasted during design and updated through experience	Continuous collection of condition monitoring data	Forecasting of remaining equipment life based on actual stress loading
Kind of Prediction	None	None	On- and off-system, near-real-time trend analysis	On- and off-system, real-time trend analysis

Maintenance Process within Legacy Logistics System

In the current situation, legacy aircraft are supported by two types of maintenance: unscheduled maintenance and scheduled (preventive) maintenance. The ground crew is only notified of a fault either prior to landing if the pilot radios in or on the ground after engine shutdown (Faas, 2003). Fault diagnosis is mainly carried out during post flight servicing, inspection and aircrew briefing. Once the problem is diagnosed, required part/parts are ordered from supply. After the parts are received, unscheduled maintenance is conducted to fix the problem. Also, maintenance personnel must document the entire process.

Regarding preventive maintenance, Time Change Item (TCI) replacements are conducted based on accumulated flight hours of the critical parts, not based on part condition (Faas, 2003). Once a part reaches its limit of accumulated flight hours, it is replaced or repaired no matter if it is still functional or not.

Maintenance Process within ALIS

As stated in the "Autonomic Logistics Concept" section, theoretically many significant changes take place within the F-35 sortie generation process with a full-functional Autonomic Logistics and Information System (ALIS). Supposedly, ALIS provides the most considerable improvement on the maintenance step by substituting a proactive approach for the existing reactive approach.

First of all, health status of the F-35 aircraft is monitored by ALIS for the entire sortie generation process. The signals coming from special sensors on the aircraft are fused via some reasoners and PHM data (including time, status of subsystems and other health related information) are transferred to the maintenance and supply units concurrently. Fault detection, fault isolation and documentation are done automatically. Therefore, maintainers are enabled to diagnose the failures more easily and quickly, and the amount of diagnostic equipment and time are reduced considerably. Since the right personnel, the right equipment, and the right part are ready at the right place at the right time, costs and delays of maintenance are minimized significantly.

Second, prognostic capabilities of ALIS replace the existing preventive maintenance with condition-based maintenance. Therefore, the time-change items which are normally replaced according to predetermined flight hours in the preventive maintenance concept will be only replaced when they become non-functional.

Additionally, ALIS provide maintainers with timely knowledge of impending failures. Therefore, opportunistic maintenance is possible by grouping multiple maintenance actions at a single time, while the aircraft is already down. For instance, a hypothetical aircraft is down for a routine engine wash. While it is being attended to, the prognostics system informs maintainers that the primary auxiliary power unit has begun to degrade and needs to be replaced within the next 15 flight hours. It also informs the maintainers that the oil in the engine is beginning to show signs of coking and has an undesirably high content of fragments. Hence, all three maintenance actions can be taken care of with a single downing of the aircraft, vice three separate maintenance actions which would keep the plane out of commission for some time (Hess & Fila, 2002).

However, in practice, ALIS is far from providing all of the theoretical benefits mentioned above. According to some official reports prepared by Government Accountability Office and The Office of The Director, Operational Test and Evaluation (DOT&E), ALIS has experienced recurring problems, including user issues and schedule delays. The integration of ALIS capabilities—which are fielded in increments—has been repeatedly delayed. Additionally, ALIS's prognostic capability still is not functional and its diagnostic system has not reached full functionality yet (Government Accountability Office, 2014; The Office of The Director, 2015).

Action Request (AR) System within ALIS

Currently, maintenance personnel track issues with ALIS through an internal reporting mechanism called the Action Request (AR) System, which allows users in the field to identify problems with the system for potential fixes (Government Accountability

Office, 2014). Upon landing, a computer system is attached to the aircraft and gathers all the information needed to decide whether the aircraft has a maintenance issue or if it is ready to fly again. If there is a problem and a known fix is not available in the F-35's Joint Technical Data (JTD), an Action Request (AR) is initiated by the maintenance personnel and sent to the Lockheed Martin engineers for tailored instructions to fix the discrepancy. After an appropriate resolution is reached, maintenance personnel fix the problem (Colbacchini, Gahafer, Mcevoy, & Park, 2016). Figure 4 represents the overall issue-resolution process.

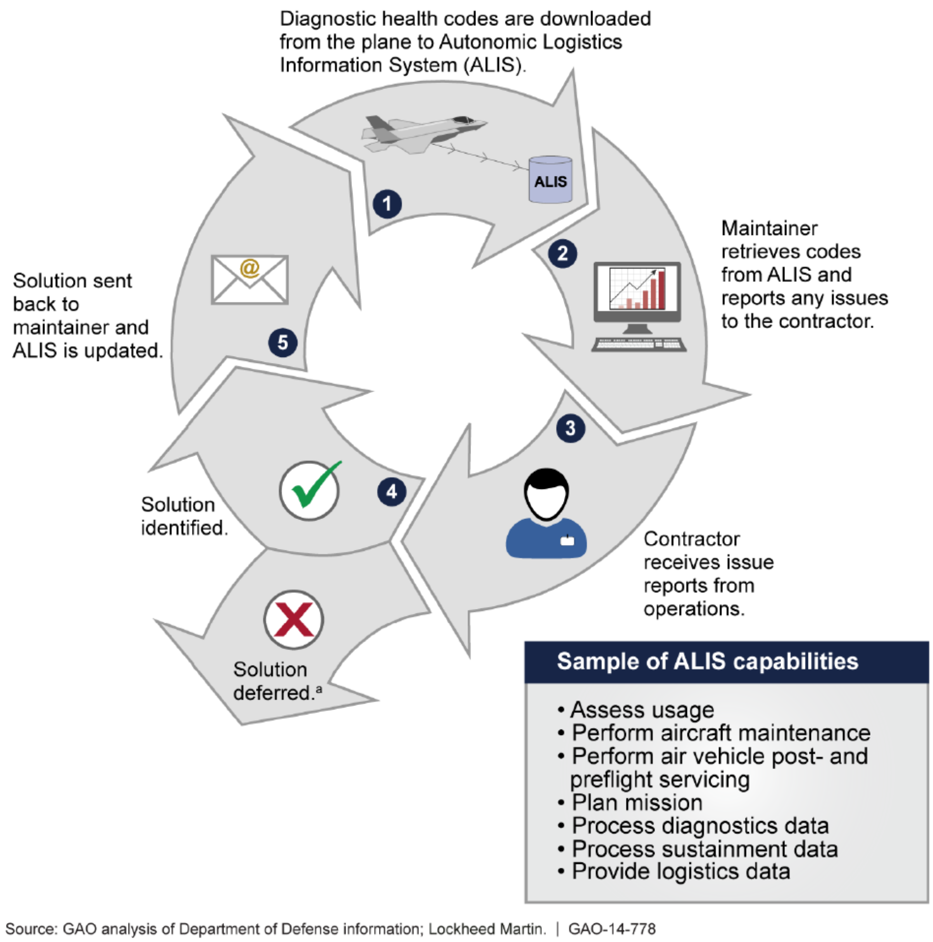


Figure 4. ALIS Issue-Resolution Process (Government Accountability Office, 2014)

The AR System aims to route and monitor ARs through the maintenance cycle efficiently. However, its current performance does not meet the desired level. Using Microsoft Excel's YASAI add-in, Colbacchini et al. (2016) developed a discrete event simulation model to determine how to minimize the time in the AR system. They found that an AR for the most severe problems took an average of 17 days to navigate through the AR system, which did not meet the Air Force standards. They concluded that maintenance personnel should increase training on the AR System and Lockheed Martin should hire more engineers to reduce the process time of ARs. A 2015 DOT&E report and a 2016 GAO report supported the findings of Colbacchini et al. by indicating that ALIS's AR process is insufficient and problematic (Government Accountability Office, 2016; The Office of The Director, 2015).

The literature reviews showed that the AR system and its effects on the sortie generation process have not been thoroughly investigated. Since it holds an important place within the F-35's current maintenance activities and causes considerable delays, it is included in our simulation model in order to obtain more realistic results.

Prognostic Health Management (PHM) within ALIS

ALIS's PHM system has three major components: fault and failure management (diagnostic capability), life and usage management (prognostic capability), and data management.

According to a 2015 DOT&E report, the F-35's PHM diagnostic and data management capabilities remain immature and the program does not yet plan to integrate prognostic capabilities. Diagnostic capabilities demonstrate poor accuracy, low detection

rates, and a high false alarm rate. Table 5 compares specific diagnostic measures from the Operational Requirements Document (ORD) with current values of performance through June 2015 (The Office of The Director, 2015).

Table 5. Metrics of F-35's Diagnostic Capabilities

METRICS OF DIAGNOSTIC CAPABILITY (6-month rolling window as of June 2015. Data provided by the Program Office are considered "preliminary" as they have not completed the formal adjudication process by the data review board.)				
Diagnostic Measure	Threshold Requirement	Demonstrated Performance		
		Block 1	Block 2	Block 3
Developmental Test and Production Aircraft				
Fault Detection Coverage (percent mission critical failures detectable by PHM)	N/A	65	73	84
Fault Detection Rate (percent correct detections for detectable failures)	98	65	73	85
Fault Isolation Rate (percentage): Electronic Fault to One Line Replaceable Component (LRC)	90	68	69	72
Fault Isolation Rate (percentage): Non-Electronic Fault to One LRC	70	76	72	79
Fault Isolate Rate (percentage): Non-Electronic Fault to 3 or Fewer LRC	90	82	87	87
Production Aircraft Only				
Mean Flight Hours Between False Alarms	50	0.20	0.60	0.18
Mean Flight Hours Between Flight Safety Critical False Alarms	450	1,360	543	170
Accumulated Flight Hours for Measures	N/A	1,360	4,886	1,360
Ratio of False Alarms to Valid Maintenance Events	N/A	44:1	16:1	1079:1

Poor diagnostic performance increases maintenance downtime. Maintainers often conduct built-in tests to see if the fault codes detected by the diagnostics are true faults. False alarms lead to unnecessary maintenance actions. These actions increase maintenance man-hours per flight hour, which in turn can reduce aircraft availability rates and sortie generation rates. Poor accuracy of diagnostic tools can also lead to desensitizing maintenance personnel to actual faults (The Office of The Director, 2015).

Because the F-35's prognostic capability is not yet functional, only the diagnostic capability is modeled in this research. The data in Table 5 are used as the baseline values to model the diagnostic process within the sortie generation process.

Learning Curves and Reliability Growth

Organizations and their workers tend to operate more efficiently over time, if they perform a task repetitively. Learning Curves (LCs) were originally proposed by Theodore Paul Wright in 1936 upon observing cost reductions due to repetitive procedures in aircraft production plants (Anzanello & Fogliatto, 2011). Figure 5 shows that it takes less cost or time to complete each additional unit as the number of repetitions (volume) increases.

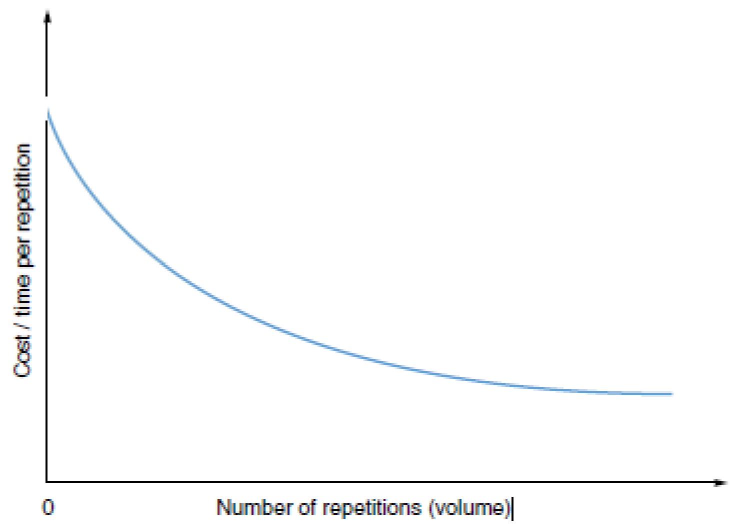


Figure 5. Learning Curve

Since their first introduction, LCs have been widely applied to services and industry. LC effects within some major U.S. industries are presented in Table 6.

Table 6. Examples of Learning Curves Effects (Cunningham, 1980)

Example	Improving Parameter	Cumulative Parameter	Learning-Curve Slope (%)
1. Model-T Ford production	Price	Units produced	86
2. Aircraft assembly	Direct labor-hours per unit	Units produced	80
3. Equipment maintenance at GE	Average time to replace a group of parts	Number of replacements	76
4. Steel production	Production worker labor-hours per unit produced	Units produced	79
5. Integrated circuits	Average price per unit	Units produced	72[a]
6. Hand-held calculator	Average factory selling price	Units produced	74
7. Disk memory drives	Average price per bit	Number of bits	76

Many approaches are used to model LCs mathematically. Generally, Wright's model, which is also referred as the "Log-linear Model", is viewed as the first formal LC model. It has the following mathematical representation:

$$y = T_1 x^b \tag{1}$$

Where:

y = the average time (or cost) per unit demanded to produce

x = the cumulative number of units produced

T_1 = the time (cost) to produce the first unit

Parameter b = the slope of the LC which describes the workers' learning rate.

= (log of the learning rate) / (log 2).

Parameter b has values between -1 and 1. Values of b close to -1 denote high learning rate and fast adaptation to task execution (Anzanello & Fogliatto, 2011). According to the model, as the cumulative number of the output is doubled, the average time (cost) per unit decreases by b percent.

As stated in previous sections, the sortie generation process is a combination of multiple repetitive tasks. Therefore, it is possible that the time required to perform these tasks may decrease as logistics personnel gain more experience after each flight mission. The 2015 DOT&E report notes that a learning curve effect is likely to improve the F-35's repair times. As maintainers become more familiar with common failure modes, their ability to quickly repair them improves over time (The Office of The Director, 2015).

Another important implication of the LCs is the reliability growth. Complex systems under development typically face high initial failure rates. However, over time a learning curve effect takes place as sources of failures are determined and eliminated. Therefore, the failure rates start to gradually decrease (Jewell, 1984).

The Duane model is one of the most common reliability growth patterns experienced in practice (Larry H . Crow, 2011). DOD also uses the Duane model to investigate the reliability growth for aircraft. Mean Flight Hours Between Unscheduled Maintenance (MHFBSME) growth rates calculated by the DOD for several historical aircraft are shown in Table 7 (The Office of The Director, 2015).

Table 7. Growth Rates for Several Historical Aircraft (The Office of The Director, 2015)

Aircraft	MFHBME Growth Rate
F-15	0.14
F-16	0.14
F-22 (at 35,000 flight hours)	0.22
B-1	0.13
"Early" B-2 (at 5,000 flight hours)	0.24
"Late" B-2	0.13
C-17 (at 15,000 flight hours)	0.35

However, due to lack of the data to implement the Duane model, this research uses the Idealized Growth Curve Model which is a simpler reliability growth model defined in the Military Handbook of Reliability Growth Management (United States Department of Defense, 1981).

According to the Idealized Growth Curve Model, a reliability growth rate is calculated through the equation below.

$$\alpha = ln\left(\frac{T}{t_1}\right) - 1 + \left\{\left[1 + ln(\frac{T}{t_1})\right]^2 + 2ln(\frac{M_F}{M_i})\right\}^{0.5} \qquad (2)$$

Where:

α = Growth parameter

T = Cumulative test time at the end of the test

t_1 = Length of initial test cycle in cumulative test time

M_F = Final Mean Time to Failure (MTTF)

M_i = Initial MTTF

The growth rate is a value between 0 and 1. Zero means no growth. As the growth rate increases, the failure rate decreases. Based on the growth rate calculated in Equation 2, instantaneous MTTF is obtained from equation 3.

$$M(t) = \begin{cases} M_1, \ 0 < t < t_1 \\ \frac{M_1}{(1-\alpha)}(\frac{t}{t_1})^{\alpha}, \ t \geq \ t_1 \end{cases} \qquad (3)$$

Where:

$M(t)$ = Instantaneous MTTF at time t

t = Cumulative test time

M_1 = Average MTTF at time t_1

t_1 = Length of initial test cycle in cumulative test time

α = Growth parameter

Due to their potential impacts mentioned above, LCs and reliability growth concepts are addressed while developing the simulation model. Necessary mathematical functions are embedded into the model accordingly. Thus, the model is able to produce more realistic outputs for the overall sortie generation process. Implementations of LCs and reliability growth are explained thoroughly in the methodology section.

Conclusion

The literature reviews indicated that many valuable studies were conducted to investigate the sortie generation process and the potential impacts of the AL system on the sortie generation MOPs. However, they mainly examined the AL system on a conceptual basis, since real world F-35 data was not yet available. Moreover, none of the researches incorporated possible impacts of the learning curves.

Incorporating the learning curves and using the most recent real world data about the AL system, this research builds a discrete event simulation model of the F-35's sortie generation processes in order to provide valuable information for decision makers.

III. Methodology

Chapter Overview

This chapter describes a discrete event simulation model of the F-35's sortie generation process under the Autonomic Logistics (AL) system. The following sections cover data collection, definition of assumptions, modeling steps, and implementation of Learning Curves (LCs) and reliability growth concepts.

Simulation in Arena

Sortie generation is a very complicated process with many sub-processes and numerous decision nodes. Performing an analytical analysis may be extremely time consuming, challenging, and even impossible in some occasions. At this point, computer based simulation tools provide great benefits to the modelers.

Arena® simulation software is used in this research to model the F-35' sortie generation process under a simplified AL system that approximates current ALIS capabilities. It is a flexible and powerful tool that allows analysts to create animated simulation models that accurately represent virtually any system (Takus & Profozich, 1997). A detailed description of the modeling process is presented in the following sections.

Assumptions

For convenience, some assumptions have been made during the model building stage. Due to the difficulty of demonstrating every activity within the F-35's sortie generation process, it is assumed that a sortie generation process consists only of the sub-

processes represented in Figure 1 and that excluded activities do not make a significant difference.

The F-35 aircraft is a complex weapon system including a large number of Line Replaceable Components (LRC). Its mission capability depends on the full functionality of all LRCs. However, from a modelling view, it is not feasible to model every LRC and failure type. For simplicity, each F-35 is assumed as a one-LRC system which encounters only mission critical failures depending on the accumulated flight hours. Also, scheduled maintenance and depot level maintenance are assumed to be conducted at predetermined intervals based on accumulated flight hours.

As stated in Chapter 2, ALIS's diagnostic capability is functional now, but the prognostic capability is not yet functional. Therefore, the prognostic capability is not included in the model. Also, analyzing the impact of resource levels on sortie generation is beyond the scope of this research. Therefore, resource capacity is assumed to be infinite for all processes. Process modules are used to delay the aircraft for predetermined time durations. Meanwhile, no resource is seized nor released by the aircraft. Thus, queuing problems do not occur.

DOD reports emphasize that there will be a learning curve and reliability growth effect on F-35's maintenance processes. However, learning rates or reliability growth rates and the processes that will be influenced by them are not explicitly known. It is assumed that while LCs have impacts on the process times of the Action Request (AR) system and maintenance activities, reliability growth influences the Mean Flight Hours Between Critical Failures (MFHBCF).

Additional assumptions include: a) The input data obtained from literature reviews and field experts adequately reflect real operations; b) A typical flight day is 24 hours and flight year is 365 days; c) Flight missions are planned at a constant rate during an assumed five-year period; d) There is no aircraft loss or accident in flight due to a failure; e) Mission critical failure is the only failure type encountered by the F-35; f) Probability of a mission critical failure during preflight inspection and final check is 0.05 and 0.01 respectively; g) Probability for running out of LRC supply is 0.50; h) For 85% of the mission critical failures, a known fix is available in the Joint Technical Documents; i) For 50% of the time, maintainers are able to detect PHM-related false alarms during the troubleshooting process; j) The aircraft in the model is the F-35's conventional variant.

Data Collection

Data collection is an important simulation step and directly affects model validity. Since the F-35 is a relatively new system, it was difficult to obtain actual data for all processes within the model. Therefore, when actual data were not available, data sets belonging to other fighter aircraft were collected and used to model the associated processes.

The majority of process delay times were taken from the "US Air Force Maintenance Capability and Capacity Modeling and Simulation Summary Technical Report" (Spencer, Hall, & Ostrander, 2010). Other process times were obtained from previous studies visited during the literature reviews (Faas, 2003; Rossetti & McGee, 2006; Sheppard, 2014). Delay times for the activities in the sortie generation process and their related statistical distributions are presented in Table 8.

Table 8. Process Times and Related Distributions

Process	Time and Distribution	Reference
Refuel	*Normal (0.5, 0.145) hours	(Spencer, Hall, & Ostrander, 2010b)
Other Servicing (Oil, Liquid oxygen, Hydraulics, or Tires)	Normal (0.3, 0.087) hours	(Spencer et al., 2010b)
Configuration (Weapon Loading or Pod Installation)	Uniform (28, 249) minutes	Adjusted from (Spencer et al., 2010b)
Pre-Flight Inspection	Triangular (50,60,70) minutes	(Faas, 2003)
Engine Start, Final Systems Check, and Taxiing	Normal (0.8, 0.232) hours	(Spencer et al., 2010b)
Takeoff	Triangular (2,3,4) minutes	(Faas, 2003)
Sortie	Normal (2, 0.5) hours	(Faas, 2003)
Landing	Triangular (14,15,16) minutes	(Faas, 2003)
Parking and Recovery	Triangular (5,7,9) minutes	(Faas, 2003)
Downloading PMD into ALIS	Triangular (7,10,13) minutes	Adjusted from (The Office of The Director, 2015)
Basic Post-Flight Operations and Aircrew Debrief	Normal (2, 0.58) hours	(Spencer et al., 2010b)
Troubleshooting	Triangular (20, 24, 30) minutes	(Faas, 2003)
Wait for Part to issue from supply	Triangular (0.5, 2, 2.5) hours	(Rossetti & McGee, 2006)
Unscheduled Maintenance	Triangular (9, 9.7, 10.4) hours	Adjusted from (The Office of The Director, 2015)
Scheduled Maintenance	Triangular (5,7,8) days	(Rossetti & McGee, 2006)
Depot Level Maintenance	Triangular (110, 131, 144) days	(Sheppard, 2014)

*Normal (Mean, Standard Deviation)

The F-35A’s maintenance data and PHM statistics were obtained from the 2015 DOT&E report and are presented in Table 9. According to this data, the F-35 PHM system has the capability of detecting 84% of the mission critical failures with 85% of those detections being correct. Furthermore, in the instance of the failure being a non-electronic fault, 79% of the correct detections are isolated successfully to a single LRC. Therefore, the PHM system can accurately detect only 71.4% of the mission critical non-electrical failures and successfully isolate only 57.1% of them to a LRC.

Table 9. Actual MFHBCF, MCMTCF, MFHBFA and PHM Data for F-35A (The Office of The Director, 2015)

Mean Flight Hours Between Critical Failures (MFHBCF)	10.2 hours
Mean Corrective Maintenance Time for Critical Failure (MCMTCF)	9.7 hours
Mean Flight Hours Between Flight Safety Critical False Alarm	170 hours
Fault Detection Coverage (percent mission critical failures detectable by PHM)	84%
Fault Detection Rate (percent correct detections for detectable failures)	85%
Fault Isolation Rate (percent isolation of Non-Electronic Fault to One LRC	79%

The AR system within the ALIS is used to provide resolutions to the problems of which known fixes are not available in the technical documents or PHM system. A 2016 study conducted by Colbacchini et al. (2016) provided some valuable data about the resolution process of Category 1 (critical) problems through the AR. Our research translates their dataset into triangular distributions used to model the AR system as presented in Table 10**.**

Table 10. Process Times within the AR System

Initiation Process	Triangular (12, 24, 30) hours
Optional Screening Point (OSP)	Triangular (12, 24, 30) hours
Required Screening Point (RSP)	Triangular (1, 2, 2.5) days
Resolution	Triangular (9, 11, 13) days

Model Development

Our simulation model represents the sortie generation process of a 16-aircraft F-35 fleet in a notional base in Turkey over a five-year period. There are 24 hours in a flight day and 365 days in a flight year. Flight missions are planned at a constant rate. If there is an available aircraft in the aircraft pool, the mission is initiated immediately. Otherwise, the mission is cancelled.

The global input variables used in the model are presented in Table 11. MFHBFA, fault coverage rate, correct fault detection rate, fault isolation rate, reliability growth rate, and learning curve rate are determined as the critical factors which are used during the design of experiment (DOE) stage. Their impacts on the sortie generation process are examined by setting them to different levels under different scenarios.

Table 11. Global Variables

Variable	Initial value	Unit
*MFHBFA	170	HOUR
MFHBCF	10.2	HOUR
MFHBDLME	2,000	HOUR
MFHBSME	400	HOUR
FLIGHT TIME	0	HOUR
*FAULT COVERAGE RATE	84	PERCENT
*CORRECT FAULT DETECTION RATE	85	PERCENT
*FAULT ISOLATION RATE	79	PERCENT
HEALTHY1	95	PERCENT
HEALTHY2	99	PERCENT
AR CORRECT	95	PERCENT
*RELIABILTY GROWTH RATE	0	PERCENT
*LEARNING CURVE RATE	100	PERCENT
PLANNED FLIGHT HOURS	0	HOUR
FLYING SCHEDULING EFFECTIVENESS RATE	0	PERCENT
AIRCRAFT AVAILABILITY RATE	0	PERCENT
SUPPLY AVAILABILITY	50	PERCENT
*KNOWN FIX AVAILABILITY	85	PERCENT

*Critical factors used in the DOE

An overall view of the simulation model is presented in Figure 6. It was built based on the sortie generation activities defined in Figure 1. The model building process is explained thoroughly in the following sections.

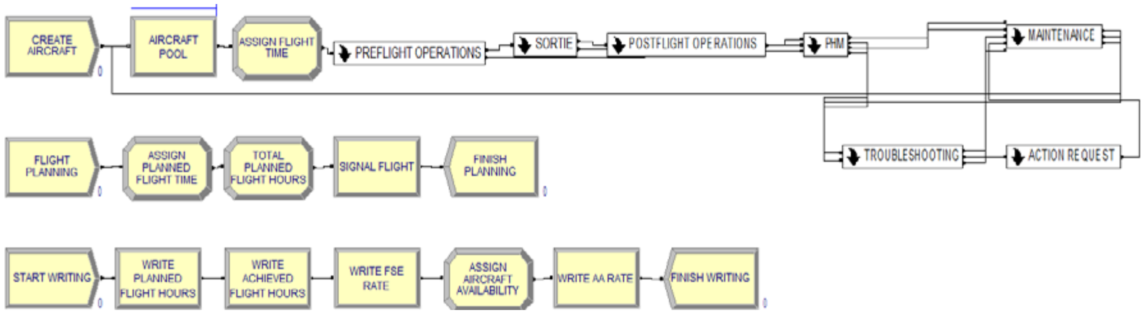


Figure 6. Sortie Generation Model

Model Initialization

The simulation model is started with the creation of 16 aircraft entities which are then routed to the aircraft pool to wait for a flight mission signal from the mission planning area. The Aircraft pool is a hold module which releases one aircraft after a mission signal is received from the flight planning area. After release, the flight duration determined in the flight planning area is assigned to the aircraft, and the aircraft goes to the preflight operations area. On completion of the sortie generation cycle, the aircraft does not leave the model; it returns to the aircraft pool and waits for the next mission.

The flight scheduling area is a combination of create, assign, signal, record, and disposal modules. A flight mission is created every hour at a constant rate. Once a flight mission is created, an assign module determines the flight duration according to a normal distribution with a mean of 2 hours and standard deviation of 0. 5 hours. Then, a mission signal is sent to the hold module to release an aircraft from the aircraft pool. If any aircraft is available, the flight mission starts. Otherwise, the flight is cancelled. After the mission is signaled, an assign module accumulates the planned flight hours and assigns it to PLANNED FLIGHT HOURS global variable. An overall view of the model initialization is presented in Figure 7.

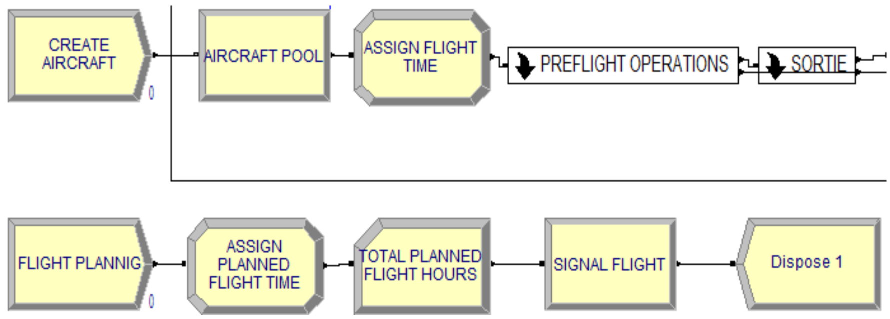


Figure 7. Model Initialization Process

Preflight Operations

After an aircraft is released from the aircraft pool, it is routed to the refueling area. Then, a decide module checks the need for additional servicing. Fifty percent of the time, the aircraft requires servicing for oil, liquid oxygen, hydraulics, or tire check. Following the servicing, a transition from one configuration to another starts. It involves alternate mission equipment download and upload and munitions upload. After the aircraft is configured, a pre-flight inspection is conducted to check if any mission critical failure is present or not. During the inspection, there is a 0.05 probability that a mission critical failure is detected. If there is a failure, the aircraft is routed to the PHM area; otherwise it is transferred to the sortie area. The overall view of the pre-flight operations is presented in Figure 8.

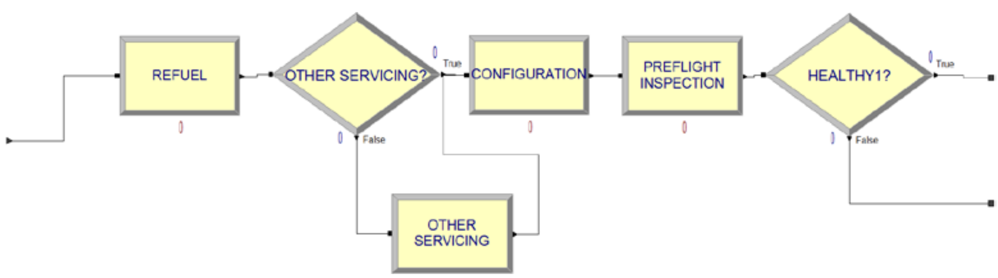


Figure 8. Pre-flight Operations

Sortie

Completing the pre-flight operations, the engine is started and final checks are conducted to detect possible mission critical failures. At this point, the probability of a mission critical failure's occurrence is 0.01. If there is a failure, the aircraft is routed to the PHM area; otherwise it releases the parking area and begins taxiing onto the runway for take-off. The aircraft takes off and the sortie is executed based on a flight duration predetermined in the mission planning area. Then the aircraft comes to the landing module and is delayed there. The overall view of the sortie is presented in Figure 9.

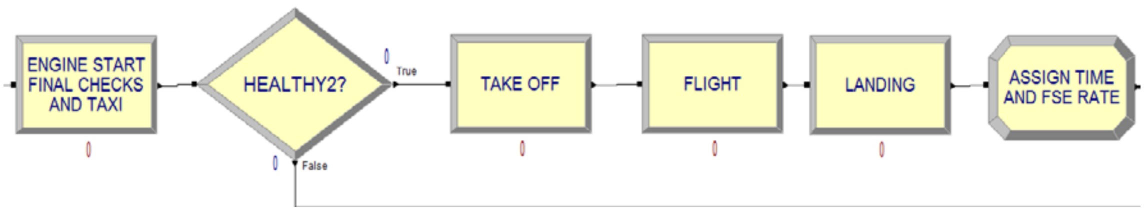


Figure 9. Sortie Process

Following the landing, an assign module calculates the flying scheduling effectiveness (FSE) rate of the fleet and assigns it to the FLYING SCHEDULING EFFECTIVENESS RATE global variable. Additionally, the attributes presented below are assigned to the aircraft. These attributes are flight hours accumulated by each aircraft. Their usages are explained in the following sections.

- AIRCRAFT MFHBCF: Flight Hours Between Critical Failures
- AIRCRAFT MFHBSME: Flight Hours Between Scheduled Maintenance
- AIRCRAFT MFHBFA: Flight Hours Between False Alarms
- AIRCRAFT MFHBDLME: Flight Hours Between Depot Level Maintenance

Post-Flight Operations

After landing, the aircraft is routed to the parking area. Then, aircrew debriefing and basic post-flight operations (BPO) are conducted concurrently. During BPO, maintainers download post flight Health Reporting Codes (HRC) from the aircraft to ALIS through a Ground Data Security Assembly Receptacle (GDR). The HRCs are used by ALIS's PHM system to check the aircraft health status.

PHM Area

Holding the fault coverage, fault detection, fault isolation and false alarm logic, the PHM area is the most crucial part of the model. It consists of a combination of assign and decision modules. The overall view of the area is represented in Figure 10.

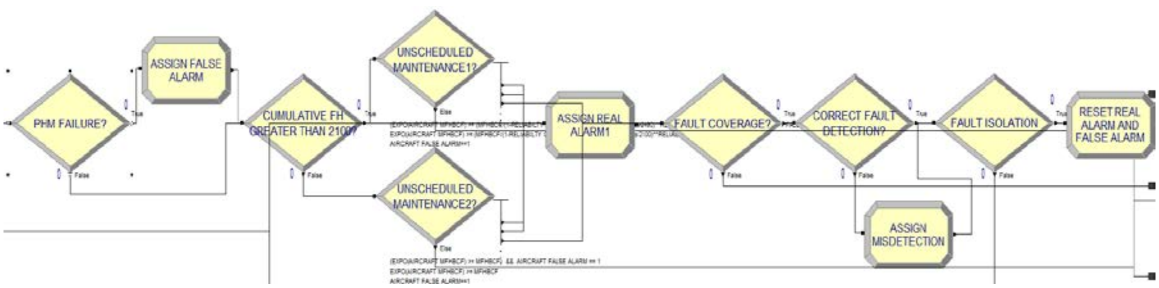


Figure 10. PHM Area

At the beginning of the PHM process, a decide module checks for false alarms. A false alarm (false positive) indicates that there is a failure given that none exists. The decide module compares the AIRCRAFT MFHBFA attribute value to a predetermined MFHBFA (170 hours) to decide whether there is a false alarm or not. If the related aircraft's AIRCRAFT MFHBFA attribute value exceeds the MFHBFA value, then a false alarm occurs. If there is a false alarm, then the value one is assigned to the AIRCRAFT FALSE ALARM attribute value; the AIRCRAFT MFHBFA attribute value is reset to

zero and the aircraft is sent to a decide module checking the fleet cumulative flight hours. Otherwise, the aircraft is directly sent to the decide module checking the fleet cumulative flight hour.

Next, a decide module checks whether the fleet cumulative flight hours are above or below the 2100-hour level, which is the starting point of reliability growth for Mean Flight Hours Between Critical Failures (MFHBCF). As presented in Table 8, currently the MFHBCF is 10.2 hours. However, after the fleet exceeds 2100 flight hours, it begins to improve. A detailed explanation for the implementation of the reliability growth is presented in the following sections.

After the reliability growth check, an unscheduled-maintenance check module compares MFHBCF to the AIRCRAFT MFHBCF attribute value and determines the current condition of the aircraft. At this point, an aircraft may be in one of the following categories: A) Critical failure, B) Critical failure and false alarm (treated as critical failure), C) False alarm, D) Healthy. Category A means that the AIRCRAFT MFHBCF attribute value exceeded the MFHBCF and a mission critical failure occurred. Category B means that both a critical failure occurred and a false alarm was assigned to the aircraft previously in the false alarm check area. Category C means that no critical failure occurred but a false alarm was assigned to the aircraft in the previous module. Category D means that the aircraft has neither a critical failure nor a false alarm.

If the aircraft is in category A or B, it is sent to an assign module and value of one is assigned to the AIRCRAFT REAL ALARM attribute value, and then the aircraft is transferred to the failure coverage check. If the aircraft is in category C, it is directly sent to the failure coverage check without being assigned a real alarm. Finally, if the aircraft is

in category D, it skips the unscheduled maintenance and directly goes to the scheduled maintenance check.

If there is a false alarm or real failure, a fault coverage check is applied to see whether the fault is covered by the PHM or not. The current PHM fault coverage rate is 0.84. If the failure is not within the PHM coverage, the aircraft is routed to the troubleshooting area for further inspections; otherwise it is transferred to another deicide module to see whether the fault detection is correct or not. The current correct detection rate of the PHM system is 0.85. If the detection is not correct, an assign module assigns value of one to attribute MISDETECTION, and then the aircraft is routed to the fault isolation check. Otherwise, the aircraft is directly sent to the fault isolation check module. Misdetection means that the aircraft has a problem, but it is defined inaccurately; therefore, an incorrect maintenance action would be applied to attempt to fix it.

After fault detection, the fault isolation module checks whether the fault can be isolated to one specific LRC or not. The current fault isolation rate of the PHM system is 0.79. If the fault can be isolated to one specific LRC, then the AIRCRAFT REAL ALARM and the AIRCRAFT FALSE ALARM attribute values are reset to zero and the aircraft is routed to the unscheduled maintenance module; otherwise the aircraft is sent to the troubleshooting area for further inspection.

Troubleshooting and Action Request

If a mission critical failure is not covered or isolated by the PHM system, then the aircraft is routed to a troubleshooting process for further inspection. After the troubleshooting, a decide module checks whether the failure is a real alarm or not. If it is a real alarm, then the AIRCRAFT REAL ALARM attribute value is reset to zero and the

aircraft is transferred to the known fix availability check. If it is a false alarm, the AIRCRAFT FALSE ALARM attribute value is reset to zero and a decide module checks whether maintainers can detect the false alarm or not. It is assumed that maintainers catch a false alarm 50 percent of the time. If the maintainers catch the false alarm, the aircraft skips the unnecessary unscheduled maintenance and directly goes to a scheduled maintenance check. Otherwise, the aircraft is routed to the known fix availability check and ends with an unnecessary unscheduled maintenance action.

After the real and false alarm checks, a decide module checks whether a known fix is available in the technical documents or not. The probability of a known fix is 0.85. If the known fix is available, the aircraft is directly sent to the unscheduled maintenance area; otherwise an action request (AR) is initiated to find a solution to the fault by the assistance of Lockheed Martin engineers. Overall views of the troubleshooting process and the AR system are represented in Figure 11 and Figure 12.

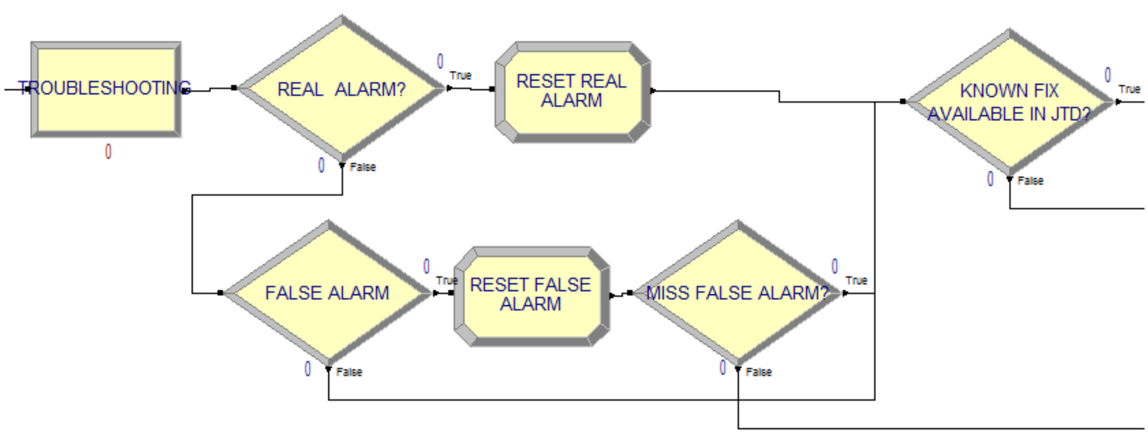


Figure 11. Troubleshooting Process

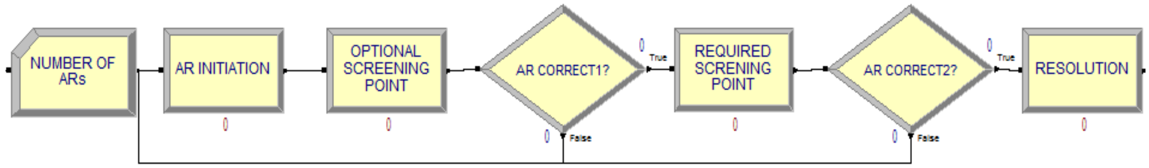


Figure 12. Action Request Process

An AR is delayed within the AR system according to the times and distributions presented in Table 10. OPS and RSP checkpoints ensure that the AR is detailed and complete before sending the AR to the Lockheed Martin engineers. There is a 0.95 probability that AR passes through these checkpoints without any problem. If there is a problem, the AR is sent back to the initiation step (Colbacchini et al., 2016). After a resolution is found, the aircraft is routed to the unscheduled area.

Colbacchini et al. (2016) indicated that current AR process times are longer than the desired values. Our research assumes that a learning curve effect takes place within the AR process. A detailed explanation is presented in the Implementation of the Learning Curves section.

Maintenance Operations

Maintenance processes consist of unscheduled maintenance, scheduled maintenance, and depot level maintenance. Figure 13 represents the overall maintenance area.

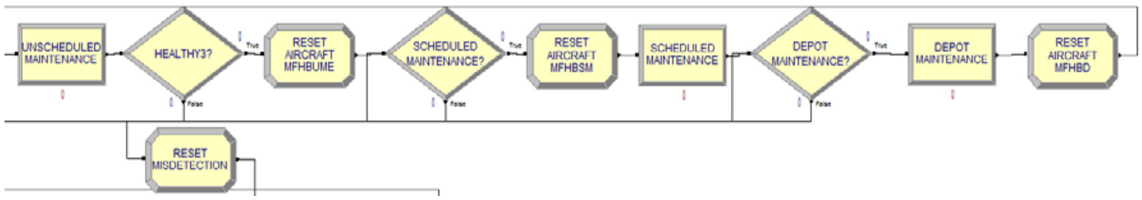


Figure 13. Maintenance Processes

Once the aircraft is routed to the unscheduled maintenance area, a record module counts the number of unscheduled maintenance. Before the maintenance, a decide module checks if there are an adequate number of LRCs or not. Fifty percent of the time, the LRC quantity is insufficient and the aircraft is delayed until replenishment arrives. If there is enough supply, the unscheduled maintenance is initiated immediately. After the maintenance is conducted, the AIRCRAFT MFHBCF attribute value is reset to zero and the aircraft is sent to a decide module for functionality check. If the MISDETECTION attribute value is one, then previous fault detection and fault isolation actions were done inaccurately by the PHM system and the wrong maintenance activity was conducted to the aircraft. Therefore, the MISDETECTION attribute value is reset to zero and the aircraft is routed to the troubleshooting module for further inspection.

If the MISDETECTION attribute value is zero, the aircraft is routed to another decide module for a scheduled maintenance check. Scheduled maintenance is conducted based on the accumulated flight hours. The default value for mean flight hours between scheduled maintenance is 400 hours and is recorded in the MFHBSME global variable. If the AIRCRAFT MFHBSME attribute value does not exceed the MFHBSME variable value, the aircraft is directly sent to depot level maintenance; otherwise scheduled

maintenance is conducted. After the scheduled maintenance, the AIRCRAFT MFHBSME is reset to zero and the aircraft is routed to depot level maintenance.

When the aircraft needs any modification or upgrade, it is sent to the depot level maintenance area. Like scheduled maintenance, depot level maintenance is also determined according to the accumulated flight hours. The default value of mean flight hours between depot level maintenance is 2000 hours and recorded in the MFHBDLME global variable. If the AIRCRAFT MFHBDLME attribute value does not exceed the MFHBDLME variable value, then the aircraft is routed directly to the aircraft pool; otherwise the aircraft undergoes depot level maintenance. After the depot level maintenance, the AIRCRAFT MFHBD is reset to zero and the aircraft is transferred to the aircraft pool.

Implementation of the Reliability Growth for the MFHBCF

The 2015 DOT&E report indicates that reliability growth takes place within the F-35 system. As shown in Table 12, while MFHBCF value for F-35A was 8.2 hours at 8,834 cumulative flight hours, it improved to 10.2 hours at 15,845 cumulative flight hours. The target value for MFHBCF at 75,000 cumulative flight hours was defined as 20 hours.

Table 12. Cumulative Flight Hours versus MFHBCF

Cumulative Flight Hours	MFHBCF
8,834 (August 2014)	8.2
15,845 (May 31 2015)	10.2
75,000 (Maturity level)	20

According to Table 12, in a 10-month period between August 2014 and May 31 2015, nearly 7,000 flight hours were accumulated by the F-35A, which equates to 700 flight hours per month. The most recent MFHBCF, 10.2 hours, was calculated based on the flight hours accumulated within a three-month rolling window starting in March 1 2015 and ending in May 31 2015. Therefore, it can be derived that, by March 1 2015, accumulated flight hours were approximately 13,745 and the remaining flight hours to maturity (75,000 flight hours) were about 61,000 hours.

If the March 1 2015 is assumed as the initial point for a reliability test, we obtain the parameter values:

Cumulative test time at the end of the test *(T)* = 6,100 flight hours

Length of initial test cycle in cumulative test time *(t_1)* = 2,100 flight hours

Final Mean Time To Failure (MTTF) *(M_F)* = 20 flight hours

Initial MTTF *(M_i)* = 10.2 flight hours

Using the data above, a reliability growth rate can be calculated using Equation 2.

$$\alpha = \ln\left(\frac{61000}{2100}\right) - 1 + \left\{\left[1 + \ln\left(\frac{6100}{2100}\right)\right]^2 + 2\ln\left(\frac{20}{10.2}\right)\right\}^{0.5} = 0.15$$

Based on this growth rate, instantaneous MFHBCF can be calculated using Equation 3.

$$MFHBCF(t) = \begin{cases} 10.2, & 0 < t < 2100 \\ \dfrac{10.2}{(1-0.15)}\left(\dfrac{t}{2100}\right)^{0.15}, & t \geq 2100 \end{cases}$$

This result indicates that until 2,100 flight hours, the MFHBCF is 10.2 hours; after 2,100 flight hours, reliability growth takes place and MFHBCF begins to improve.

Anticipated MFHBCF values are presented in Table 13 for some cumulative flight hour levels when the growth rate is assumed to be 0.15.

Table 13. Reliability Growth for MFHBCF

MFHBCF	Cumulative Flight Hours
12.7	3,000
13.8	5,000
15.2	10,000
16.2	15,000
16.9	20,000
18.8	40,000
19.9	60,000

In the simulation model, reliability growth rate was defined as a global variable with a default value of zero. Equation 3 was embedded into the decide module that checks the unscheduled maintenance need caused by the mission critical failures. During the design of experiment stage, reliability growth's impact on the sortie generation performance measures is investigated by changing the growth rate under different scenarios.

Implementation of the Learning Curves

Colbacchini et al. (2016) indicated that current AR process times are longer than the desired values. These delay times considerably increase the aircraft downtime, since the aircraft is in a non-mission capable state until a resolution is found for the AR. However, Chapter 2 notes that it is possible that the time required to perform AR tasks may decrease as maintenance personnel gain more experience after each AR initiation.

Therefore, Equation 1 is embedded into the related AR process modules to implement a learning curve (LCs) effect on the AR activities. Learning rate is defined as

a global variable with a default value of one which means there is no learning from experience. During the design of experiment stage, LCs' impact on the sortie generation performance measures is investigated by changing the learning rate under different scenarios. Assuming a 95% learning rate, possible change in the average time of the resolution process is presented in Table 14.

Table 14. Impact of a 95% Learning Rate on the Resolution Time

Time (days)	Number of Repetitions
13.00	1
12.35	2
11.98	3
11.15	8
10.64	15
10.11	30
9.25	100
8.21	500

The second place for a potential LC effect is within unscheduled maintenance. Presently, the Mean Corrective Maintenance Time for Critical Failure (MCMTCF) is 9.7 hours, while the desired value is 4 hours. The 2015 DOT&E report highlights that learning curve effect is likely to improve the F-35's repair times. As maintainers become more familiar with common failure modes, their ability to repair them more quickly improves over time (The Office of The Director, 2015). Therefore, a second LC function is embedded into the unscheduled maintenance module. Assuming a 95% learning rate, possible change in the average unscheduled maintenance process time is presented in Table 15.

Table 15. Impact of the 95% Learning Rate on the MCMTCF

Time (hours)	Number of Repetitions
9.70	1
9.22	2
8.18	10
7.26	50
6.12	500
5.82	1,000
5.53	2,000
5.25	4,000
4.99	8,000

Model Verification and Validation

Model verification and validation are vital steps for a simulation study to provide realistic outputs. Even a simple structural mistake or logic error may cause the results to dramatically deviate from their true values. To build the model correctly, the entire sortie generation process was divided into relatively simpler sub processes and each sub process was developed individually. Complexity was added to the model gradually and each major addition was saved as a different version to avoid potential data loss. The model was animated frequently to check whether the aircraft flowed through the modules reasonably or not. That was very helpful to detect the errors in the model logic. After the model was complete, it was run for 30 replications to check if it produced a flying scheduling effectiveness (FSE) rate similar to the real world data obtained from the 2015 DOT&E report, when the aircraft availability (AA) rate was close to the real-world data. Logically, when the model produced AA rates close to real world data (51%), we expected the FSE rate also to be close to the real world data. The comparisons in the

Table 16 show that at an AA rate close to the real world data, our model produces a FSE rate reasonably close to the real-world data.

Table 16. Real World FSE Rate versus Simulation FSE Rate

Real World Data		**Simulation Result**	
AA Rate (%)	FSE Rate (%)	AA Rate (%)	FSE Rate (%)
51	65	49.47	69.28

For the model validation, three subject matter experts (SME) were consulted. Based on their evaluations and suggestions, some important changes in the process flows and input data were made to meet the operational needs of the air force. Moreover, official ALS reports and Air Force documents were used to ensure an acceptable level of model validity. Therefore, it was decided that the model was appropriate for the needs of the Air Force.

Conclusion

The simulation model in this study was built to represent the sortie generation process of an F-35A fleet under ALS. Actual condition of the ALS was taken into consideration rather than the theoretical expectations, since ALIS does not yet meet the desired level of functionality. During the model building stage, the main attention was given to the PHM system and the AR system due to their uniqueness to the F-35. Only mission critical failures were considered, since most of the available F-35 data was related to them.

Literature reviews indicated that little prior research was conducted examining the impact of the learning curves and reliability growth on the sortie generation process. However, as the 2015 DOT&E report indicated, it is very likely that the F-35 will be

influenced by these concepts. Therefore, appropriate LCs and reliability growth equations were embedded into the model.

This chapter thoroughly explained the data collection, model building, and implementation of the LCs and reliability growth. Results obtained from the simulation model and their related analyses are presented in the following chapter.

IV. Analysis and Results

The previous chapter explained the simulation modeling of the F-35's sortie generation process. This chapter covers the steps which are followed to obtain and analyze the simulation results. These steps include defining the key performance measures of the sortie generation process, building a designed experiment, and statistically analyzing the experimental outputs.

Measures of Performance (MOP) for the Sortie Generation Process

Literature reviews showed that aircraft reliability, aircraft maintainability, and aircraft availability are some critical MOPs used to evaluate the performance of an air force logistics system.

Aircraft reliability is related to failure frequency encountered by the aircraft. Its assessment includes a variety of metrics like Mean Flight Hours Between Critical Failure, Mean Flight Hours Between Removal, and Mean Flight Hours Between Maintenance Events. Each metric characterizes a unique aspect of overall weapon system reliability.

Aircraft maintainability is a measure to assess the amount of the time needed to repair an aircraft to return it to flying status again. Its main metric is the Mean Time To Repair.

Aircraft availability (AA) rate is determined by measuring the percent of time that an individual aircraft is in the "available" status, aggregated over a reporting period (The Office of The Director, 2015). The aircraft which are not available are assigned to one of three categories: Not Mission Capable for Maintenance, Not Mission Capable for Supply, or Depot status.

For this research, AA rate and flying scheduling effectiveness (FSE) rate were chosen as the key MOPs of the F-35's sortie generation process. FSE rate is calculated by dividing the total flight hours to the total planned flight hours and it is directly related to the AA rate. While high availability rates ensure more flight hours achievement, low availability rates prevent the fleet from achieving the planned flight hour goals.

Run Length and Replication

The simulation run length was determined as 5 years and 24 hours a day to allow each aircraft to go through depot level maintenance at least once. Moreover, this run length was useful to see the impacts of the learning curves and reliability growth in the long term.

After deciding the simulation run length, the second step was to determine the number of replications adequate to obtain accurate results from the simulation experiment. Literature reviews showed that there is no simple guidance on the number of replicates needed. Although more replication leads to more successful analysis, cost or time considerations often dictate the number of replicates that can be achieved. Previous simulation studies generally used 20 to 30 replications. For this research, an initial replication number was selected as 30 rather than 20 since the additional computation time between 20 replications and 30 replications was minimal.

Next, a pilot experiment was conducted to check whether 30 replications were enough to obtain normally distributed output data or not. Then, output data were imported into the JMP® Software, and Shapiro-Wilk goodness of fit (GOF) test was applied to their residuals. As presented in Appendix A, both FSE rate and AA rate passed

the GOF test at the alpha level of 0.05. Moreover, distribution graphs of the residuals appeared to have an acceptably normal bell shaped curve. Therefore, it was decided that 30 replications were adequate to carry out a successful experiment.

Design of Experiment

The literature review identified that learning curves, reliability growth, and PHM related factors had the potential of influencing the MOPs. Therefore, after randomly changing these candidate variables, several pilot simulation runs were executed to gain a better insight into their behaviors. Based on the initial findings, the following seven factors were determined as critical: Learning curve rate (LCR), reliability growth rate (RGR), Mean Flight Hours Between False Alarms (MFHBFA), Fault Coverage Rate (FCR), Correct Fault Detection Rate (CFDR), Fault Isolation Rate (FIR), and Known Fix Availability Rate (KFAR). Next, the factor count was decreased to three by combining MFHBFA, FCR, CFDR, FIR, and KFAR into a single PHM composite factor to reduce the combinatorial growth of possible experiment treatments. After determining the most important factors, their associated levels were set based on the literature reviews, official reports, and expert views (see Table 17).

Table 17. Critical Factors and Their Associated Levels

Factor / Level	**Low**		**Medium**		**High**	
PHM	PHM1		PHM2		PHM3	
	MFHBFA	*170*	*MFHBFA*	*270*	*MFHBFA*	*370*
	FCR	*84%*	*FCR*	*90%*	*FCR*	*95%*
	CFDR	*85%*	*FCDR*	*90%*	*FCDR*	*95%*
	FIR	*79%*	*FIR*	*85%*	*FIR*	*90%*
	KFAR	*85%*	*KFAR*	*90%*	*KFAR*	*95%*
Reliability Growth Rate (RGR)	RGR1	0.00	RGR2	0.10	RGR3	0.20
Learning Curve Rate (LCR)	LCR1	1.00	LCR2	0.95	LCR3	0.90

Note that when the RGR and LCR factors are both set at their low levels, a system is represented with no reliability growth and no task learning curve time reductions.

Since there were three factors with three levels, a full factorial design was selected to examine all possible combinations of the factors and find out the cause and effect relationships between them and MOPs. As presented in Table 18, 27 experiment runs or simulation scenarios were obtained as a result of the 3x3x3 full factorial design.

Table 18. Design of Experiment

Run / Factor	PHM level	Reliability Growth Rate (RGR)	Learning Curve Rate (LCR)
111	PHM1	RGR1	LCR1
112	PHM1	RGR1	LCR2
113	PHM1	RGR1	LCR3
121	PHM1	RGR2	LCR1
122	PHM1	RGR2	LCR2
123	PHM1	RGR2	LCR3
131	PHM1	RGR3	LCR1
132	PHM1	RGR3	LCR2
133	PHM1	RGR3	LCR3
211	PHM2	RGR1	LCR1
212	PHM2	RGR1	LCR2
213	PHM2	RGR1	LCR3
221	PHM2	RGR2	LCR1
222	PHM2	RGR2	LCR2
223	PHM2	RGR2	LCR3
231	PHM2	RGR3	LCR1
232	PHM2	RGR3	LCR2
233	PHM2	RGR3	LCR3
311	PHM3	RGR1	LCR1
312	PHM3	RGR1	LCR2
313	PHM3	RGR1	LCR3
321	PHM3	RGR2	LCR1
322	PHM3	RGR2	LCR2
323	PHM3	RGR2	LCR3
331	PHM3	RGR3	LCR1
332	PHM3	RGR3	LCR2
333	PHM3	RGR3	LCR3

Output Analysis

Tests of the ANOVA Assumptions

Designing a 3x3x3 full factorial DOE, each scenario was replicated for 30 times and output data were transferred into the JMP for further statistical analyses. ANOVA was the main analysis applied to the data. At the beginning of the ANOVA, following assumptions were checked to see whether it was appropriate to use ANOVA or not: 1) Normality, 2) Constant variance, 3) Independence.

The first assumption check was the normality of residuals. After all experiments were completed, Shapiro-Wilk Goodness of Fit test was applied to the residuals of FSE rate and AA rate. As presented in Figure 32 and Figure 33 in Appendix B, at the alpha level of 0.05, neither of them passed the test. However, their distribution histograms visually appeared normal. Therefore, it was assumed that residuals of the MOPs were approximately normally distributed.

Secondly, the assumption of constant variance was checked. Scatter plots of the FSE rate and AA rate in Figure 34 and Figure 35 in Appendix B demonstrated that residuals were homogenous throughout the sample and variability in the measurement error was constant.

Lastly, independence was checked. Residuals' overlay plots in Figure 36 and Figure 37 in Appendix B illustrated that residuals were not following a trend. Therefore, it was decided that the assumption of independence was satisfied.

ANOVA Analysis for AA Rate

After assumptions were tested, ANOVA analysis was conducted to examine the effects of the factors on the MOPs. Then, the research questions determined in Chapter 1 were answered.

First, the AA rate was analyzed. The ANOVA analysis of the AA rate in Table 19 shows that the model explains nearly 99.2 percent of the total variability. Overall F-Test's p-value is smaller than 0.05, which means that the model is statistically significant at the 95% level in explaining the variability in the AA rate.

Table 19. ANOVA Results for the AA Rate

Summary of Fit

RSquare	0.992529
RSquare Adj	0.992359
Root Mean Square Error	0.006066
Mean of Response	0.653882
Observations (or Sum Wgts)	810

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	18	3.8666639	0.214815	5837.830
Error	791	0.0291064	0.000037	Prob > F
C. Total	809	3.8957703		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	8	0.00826103	0.001033	38.7879
Pure Error	783	0.02084540	0.000027	Prob > F
Total Error	791	0.02910643		<.0001*
				Max RSq
				0.9946

The effect tests in Table 20 show that all factors and their associated two-way interactions have statistically significant impacts on the AA rate at the 95% level. Having the highest F Ratio, PHM is the most influential factor on the AA rate.

Table 20. Effect Tests for AA Rate

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
PHM level	2	2	1.9823738	26936.62	<.0001*
RG rate	2	2	0.2538052	3448.721	<.0001*
LC rate	2	2	1.5777275	21438.26	<.0001*
PHM level*RG rate	4	4	0.0062650	42.5644	<.0001*
PHM level*LC rate	4	4	0.0356717	242.3548	<.0001*
RG rate*LC rate	4	4	0.0108208	73.5166	<.0001*

Following the effect tests, plots of the Least Squares (LS) Means were produced and a Tukey test was conducted. While the LS Means plot is a visual test to see the relative differences in the response, a Tukey test provides a quantitative test serving the same purpose.

LS Means plots in Figure 14 visually show each factor's individual impact on the AA rate. According to these plots and Tukey tests in Appendix C, all factors have statistically significant impact on the AA rate. Moreover, the PHM level and LC rate have greater influence on the AA rate than does RG rate.

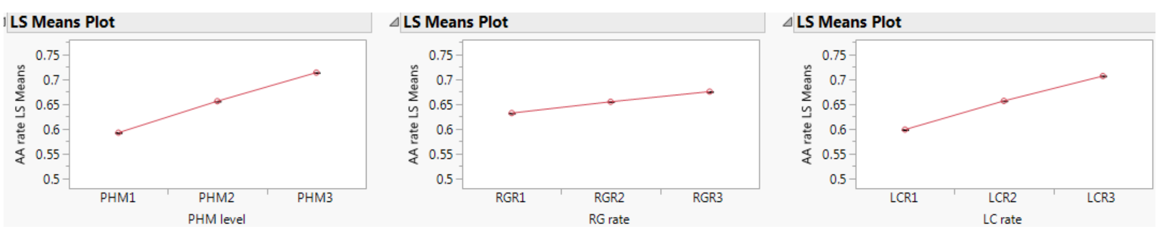


Figure 14. LS Means Plots of the Factors

Figure 15, Figure 16, and Figure 17 depict two-way interactions of the factors and their associated impacts on the AA rate. Both these plots and Tukey tests presented in

the Appendix C indicate that two-way interactions have statistically significant differences at all levels.

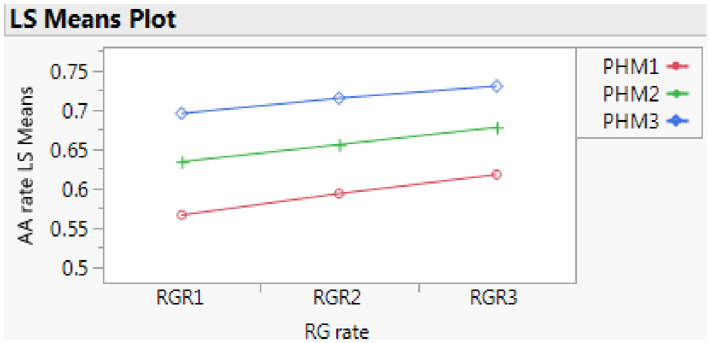


Figure 15. LS Means Plot of the PHM -RG Rate Interaction

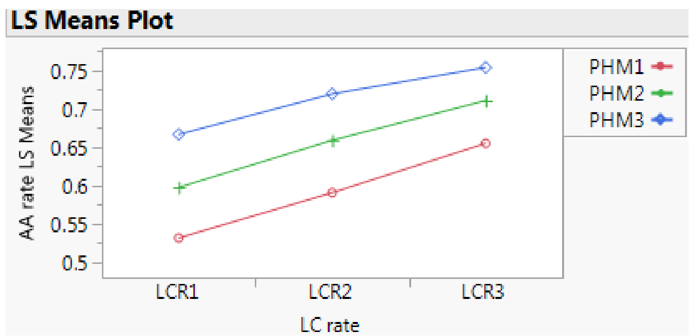


Figure 16. LS Means Plot of the PHM -LC Rate Interaction

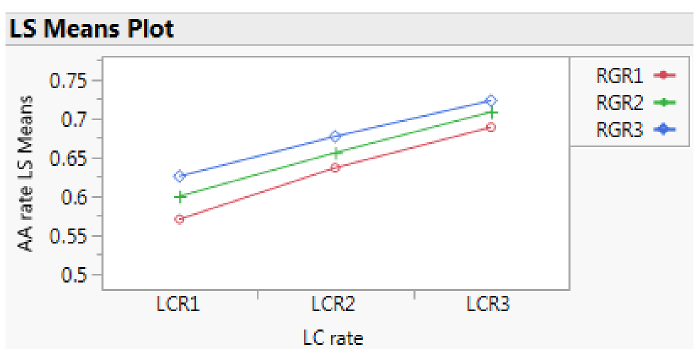


Figure 17. LS Means Plot of the RG Rate-LC Rate Interaction

AA rates which were achieved under 27 different scenarios are charted in Figure 18 labeled with levels for PHM, RG rate, and LCR rate. Supporting the ANOVA analysis and effect tests, Figure 18 also demonstrates that all factors and their associated levels significantly affect the AA rate. When each factor's individual impact is examined in Figure 18, the PHM and LC rate seem more significant than the RG rate. Additionally, the lowest AA rate is realized as 49.47%, when all factors are at low values (111 run) and the highest AA rate is realized as 76.36%, when all factors are at high levels (333 run).

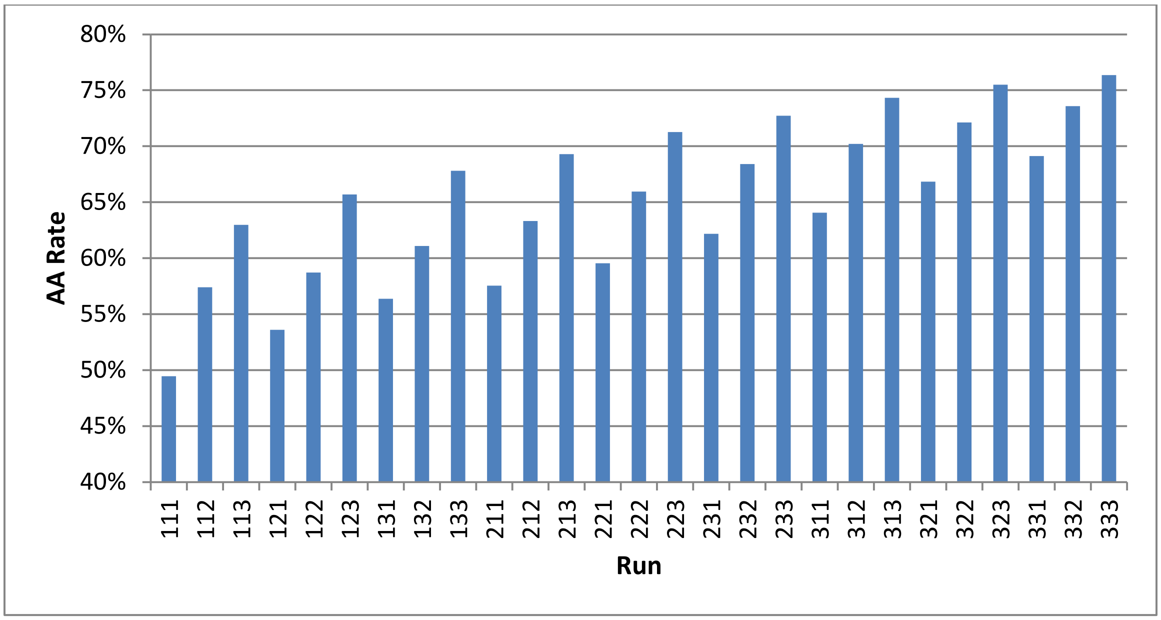


Figure 18. AA Rates under Different Factor Combinations

ANOVA Analysis for FSE Rate

As presented in Table 21, the adjusted R Square value of the model is almost 97.9 percent, which means that the model explains 97.9 percent of the total variability. The overall F-Test's p-value is smaller than 0.05, which indicates that the model is statistically significant at the 95% level in explaining the variability.

Table 21. ANOVA Results for the FSE Rate

Summary of Fit

RSquare	0.979669
RSquare Adj	0.979206
Root Mean Square Error	0.004578
Mean of Response	0.787194
Observations (or Sum Wgts)	810

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	18	0.79879037	0.044377	2117.481
Error	791	0.01657744	0.000021	Prob > F
C. Total	809	0.81536781		<.0001*

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	8	0.00385525	0.000482	29.6594
Pure Error	783	0.01272218	0.000016	Prob > F
Total Error	791	0.01657744		<.0001*
				Max RSq
				0.9844

The effect tests in Table 22 show that all factors and their associated two-way interactions are statistically significant on the FSE rate. Having the highest F Ratio, the PHM is the statistically most significant factor.

Table 22. Effect Tests for FSE Rate

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
PHM level	2	2	0.31681864	7558.574	<.0001*
RG rate	2	2	0.05460011	1302.635	<.0001*
LC rate	2	2	0.28555239	6812.632	<.0001*
PHM level*RG rate	4	4	0.01612347	192.3347	<.0001*
PHM level*LC rate	4	4	0.11056090	1318.866	<.0001*
RG rate*LC rate	4	4	0.01513487	180.5418	<.0001*

The LS Means plots in Figure 19 show each factor's individual impact on the FSE rate. As the plots depict, PHM and LC rate have greater influence on the FSE rate than does RG rate. However, their impacts diminish as their levels are increased. Tukey tests

presented in Appendix D also indicate that all levels of every factor significantly affect the FSE rate.

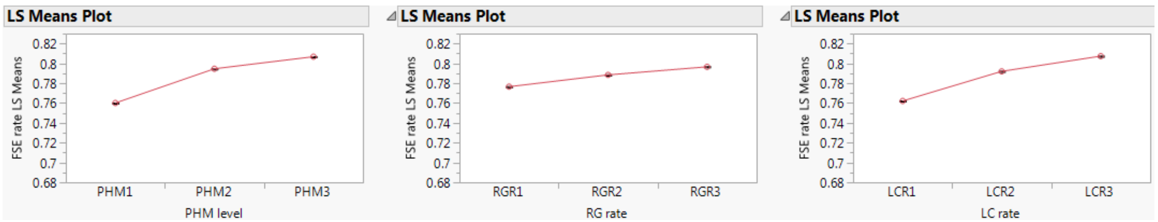


Figure 19. LS Means Plots of the Factors

Figure 20 represents the LS Means plot of PHM-RG rate interactions. According to the plot, when the PHM level is PHM3, the impact of RG rate on the FSE rate is minimal. Furthermore, Tukey tests in the Appendix D indicate that there is no statistically significant difference between (PHM2-RG3) and (PHM3-RGR1).

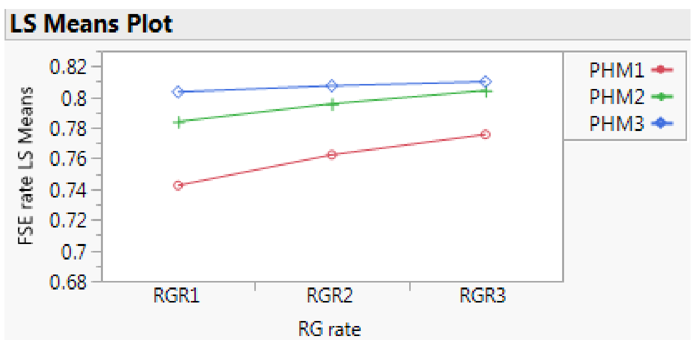


Figure 20. LS Means Plot of the PHM Level-RG Rate Interaction

The LS Means plot of the PHM level-LC rate interactions in Figure 21 shows that when the PHM level is increased, the LC rate affects the FSE rate at a diminishing rate. Moreover, at the PHM3 level, increasing the LC rate from LCR2 to LCR3 does not change the FSE rate significantly. Supporting this, a Tukey test in Appendix D shows that

there is no statistically significant difference between the following factor interactions: (PHM2-LCR3), (PHM3-LCR3), (PHM3-LCR2), (PHM3-LCR1) and (PHM1-LCR3).

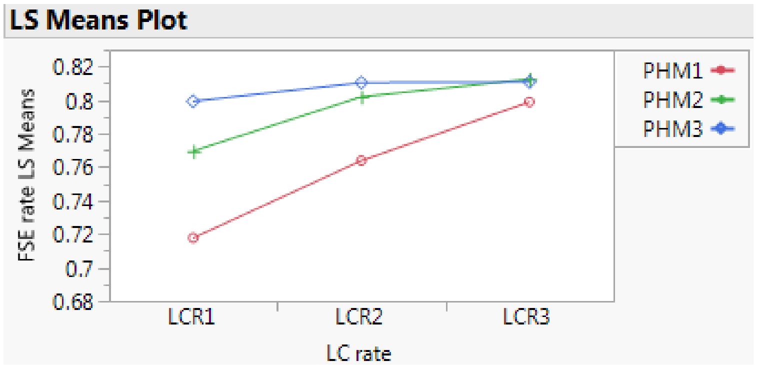


Figure 21. LS Means Plot of the PHM Level-LC Rate Interaction

The LS Means plot of the LC rate-RG rate interactions in Figure 22 demonstrates that when the RG rate is increased, the LC rate effect on the FSE rate diminishes slightly. Similarly, when the LC rate is increased, the effect of the RG rate on the FSE diminishes slightly. According to the Tukey test in Appendix D, there is no statistically significant difference between the (RGR1-LCR3) and (RGR3-LCR2) interactions.

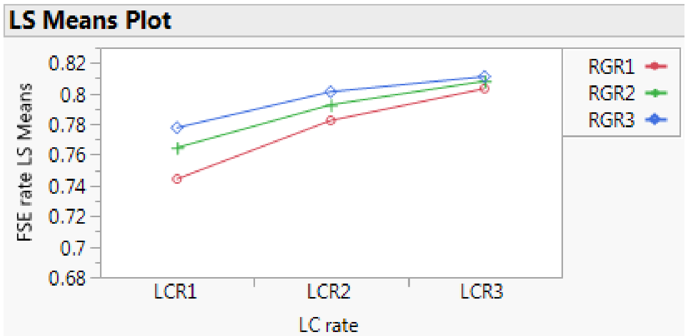


Figure 22. LS Means Plot of the RG Rate-LC Rate Interaction

The FSE rates achieved under the 27 different scenarios are charted in Figure 23 labeled with levels for PHM, RG rate, and LC rate. Parallel to the ANOVA analysis and

effect tests, this figure also shows that all factors and their associated levels significantly affect the FSE rate. The lowest FSE rate is realized as 69.28%, when all factors are at low levels (111 run). As for the highest FSE rate, it is realized as 81.41% in the 233 run, when the PHM level is medium and other factors are high. This result is not surprising, since it supports Figures 21 and 22 which demonstrate that at PHM3, high levels of LC rate and RG rate do not significantly affect the FSE rate.

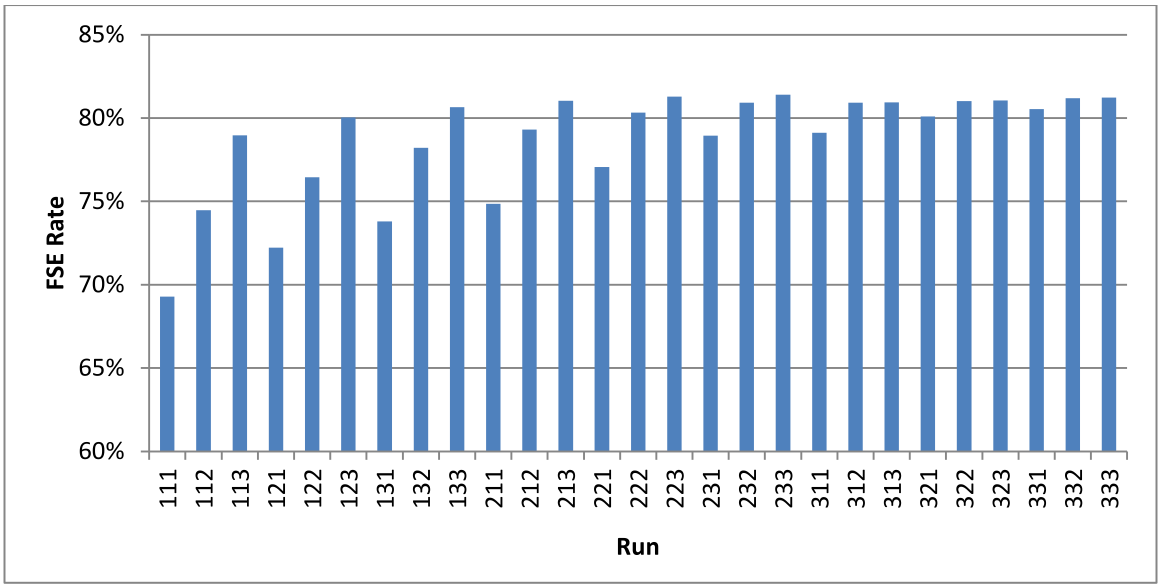


Figure 23. FSE Rates under Different Factor Combinations

Analysis of the PHM Level

As stated in the DOE section, the PHM composite factor is a combination of five sub-variables: Mean Flight Hours Between False Alarms (MFHBFA), Fault Coverage Rate (FCR), Correct Fault Detection Rate (CFDR), Fault Isolation Rate (FIR), and Known Fix Availability Rate (KFAR). The results of ANOVA analysis indicated that the PHM was the most significant factor on both FSE rate and AA rate. Therefore, some further analysis was conducted to investigate the individual impact of its sub-variables on

the sortie generation process. For this purpose, RG rate and LC rate were set to their initial values and some one-factor scenarios were examined.

First, effects of false alarms on the total unscheduled maintenance time were investigated by assigning some arbitrary values to MFHBFA global variable in the simulation model while all other factors were kept constant. As shown in Figure 24, when the MFHBFA is increased, total time spent for unscheduled maintenance decreases since unnecessary maintenance is avoided. The decrease in the maintenance time occurs at a diminishing rate. After the MFHBFA reaches 70 hours, the improvement in the maintenance time dramatically slows down; after 370 hours, it almost stops, which means the false alarms number is very low and they are not significant in the model. Like total maintenance time, FSE rate and AA rate improve diminishingly, as MFFBFA is increased gradually over time (See Figure 25).

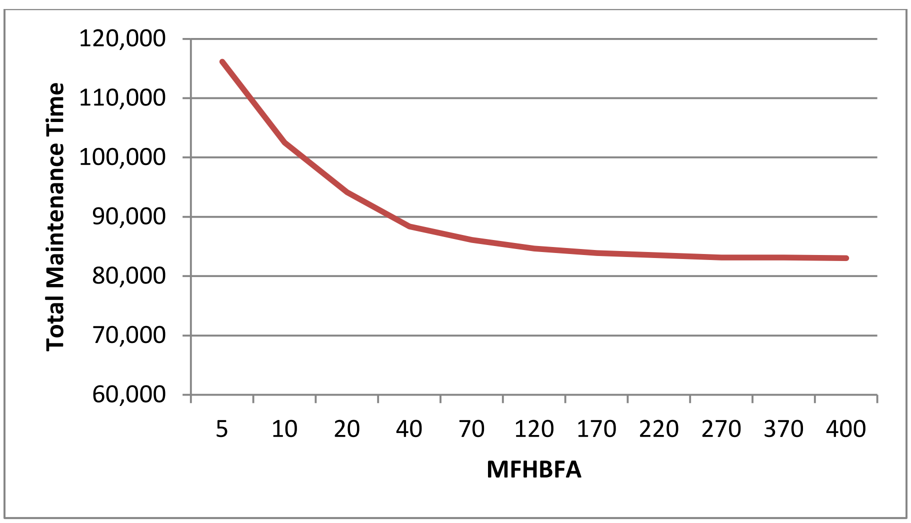


Figure 24. Total Maintenance Time vs. MFHBFA

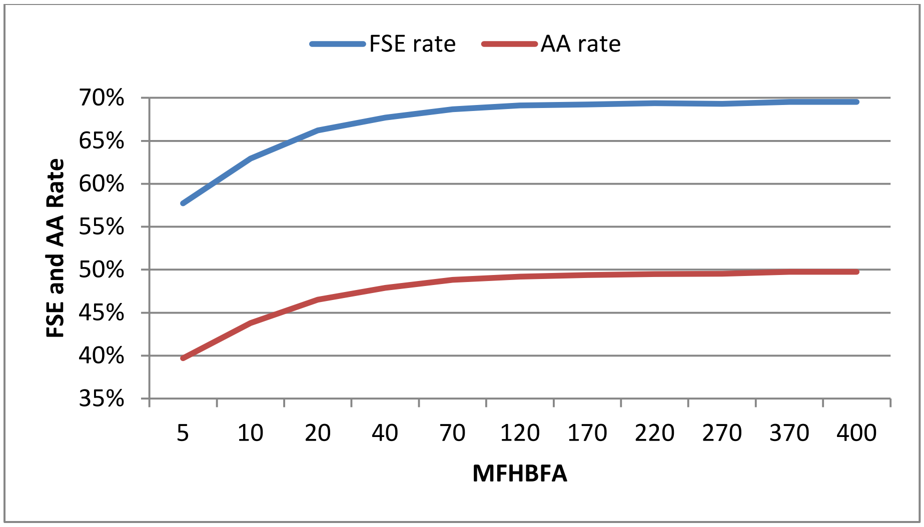


Figure 25. Impact of MFHBFA on the FSE Rate and AA Rate

ANOVA results in Appendix E also support the findings in Figure 24 and 25. They show that increasing the MFHBFA from 170 hours to 370 hours provides only small statistically significant improvements in the maintenance time, AA rate, and FSE rate.

Secondly, individual impacts of the FCR, CFDR, FIR and KFAR were examined. To see their impact on the MOPs, they were individually set to three different levels and the simulation model was replicated 30 times. Figures 26, 27, 28, and 29 illustrate their impacts on the FSE rate and AA rate, and Appendices F to I include their associated ANOVA analyses. Both the figures and ANOVA results indicate that all sub-variables have statistically significant impacts on the MOPs. Furthermore, the KFAR is the most significant one among them. When the KFAR is increased from 85% to 95%, AA rate improves from 49.47% to 58.7% and FSE rate improves from 69.28% to 76.19%. This finding supports the importance of the completeness of the F-35’s technical documents.

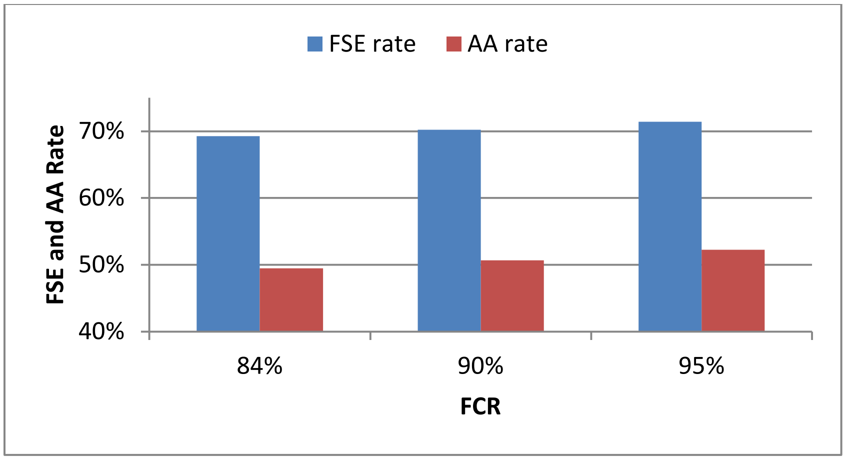


Figure 26. Impact of FCR on the FSE Rate and AA Rate

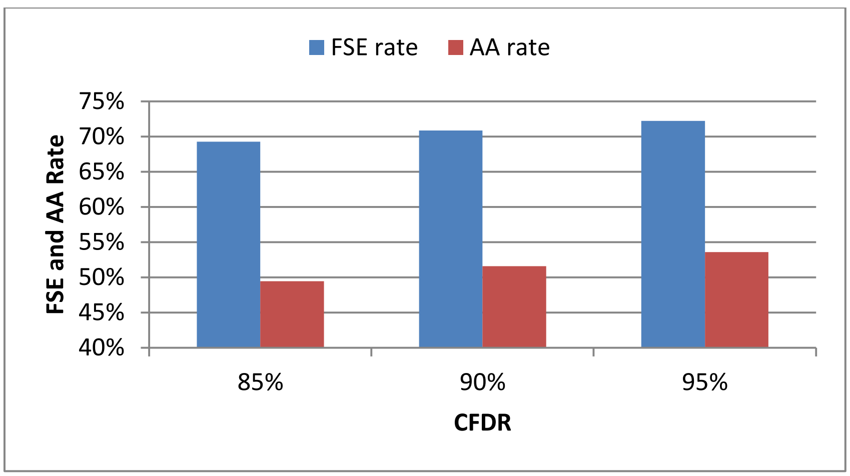


Figure 27. Impact of CFDR on the FSE Rate and AA Rate

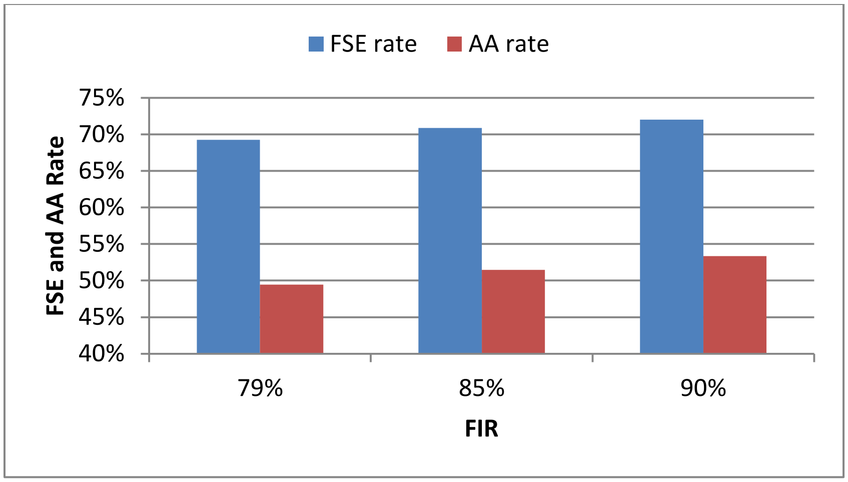


Figure 28. Impact of FIR on the FSE Rate and AA Rate

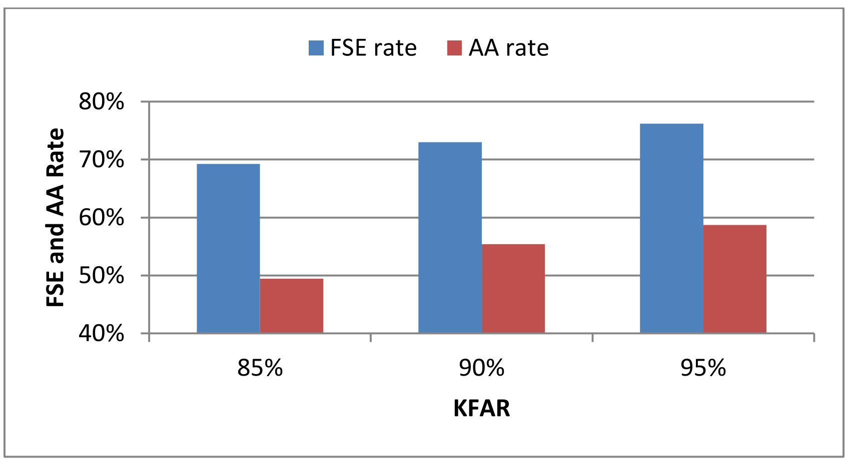


Figure 29. Impact of KFAR on the FSE Rate and AA Rate

Conclusion

This chapter started with a definition of the key measures of performance (MOP) and continued with the development of a designed experiment. The DOE was built as a 3x3x3 full factorial design and all possible combinations of the three factors were replicated for 30 times through the simulation model. Then, ANOVA analyses were

conducted to investigate the effects of the factors on the MOPs. Additionally, some further analyses were conducted to examine the individual impacts of the PHM's sub-variables. Therefore, it was demonstrated that all factors were significantly influential on the MOPs. The next chapter summarizes the research and gives recommendations for further studies.

V. Conclusions and Recommendations

Introduction

Previous chapters described the research topic, provided related literature reviews, explained the simulation model, defined the MOPs and critical factors, and analyzed the model outputs. This chapter summarizes the overall research, explains the results and gives recommendations for future research.

Research Summary

This research investigated the sortie generation process of sixteen F-35 aircraft under an autonomic logistics system at a notional base in Turkey. For this purpose, a discrete event simulation model of the sortie generation process was built in Arena® software. The key parts of the model were developed in view of the most recent practices regarding the F-35 and its logistics system.

Based on the literature researches and expert views, the aircraft availability rate and flying scheduling effectiveness rate were determined as the key measure of performance (MOP) for the sortie generation process. PHM level, reliability growth rate, and learning curve rate were chosen as the critical factors potentially affecting these measures. Then, a 3x3x3 full factorial experiment was designed to analyze the simulation outputs. The simulation run length was determined as five years (1825 days) of 24-hour operations and each of the 27 scenarios were replicated 30 times. Simulation outputs were imported to JMP® software and ANOVA analysis was conducted to see the possible cause and effect relationships between factors and MOPs.

Research Conclusion

The literature reviews indicated that the AL concept has been a popular research subject since the first introduction of the F-35. However, most prior studies investigated the AL concept from a notional basis due to a lack of real world data.

Initial delivery of the F-35s will be made to Turkey in the near future. However, official reports show that ALIS is still far from achieving the desired level of PHM functionality. Presently, the prognostic capability of the PHM system is not functional, and diagnostic capability is functional only with serious malfunctions. Keeping these realities in mind, this study aimed to explain sortie generation process of the F-35 using actual data.

For this purpose, critical factors were determined and their potential impacts on the sortie generation process of the F-35 were examined in term of AA rate and FSE rate. The relationship between critical factors and MOPs were analyzed through ANOVA.

The ANOVA results in Chapter 4 showed that all factors and their possible interactions had statistically significant impact on the AA rate. The lowest AA rate was obtained as 49.06% at the PHM1-RGR1-LCR1 treatment, when all factors were at their low levels. The highest AA rate was achieved as 76.26% at PHM3-RGR3-LCR3 treatment, when all factors were set to their high levels.

Also, all factors were statistically significant on the FSE rate. However, there were not significant differences between some of their interactions. When the PHM level was increased from PHM2 to PHM3, changes in the RG rate and LC rate did not significantly affect the FSE rate. Parallel to this finding, the highest FSE rate was achieved as 80.24% at PHM2-RGR3-LCR3 treatment, when PHM level was medium,

and other factors were high. The lowest FSE rate was realized as 67.63% at PHM1-RGR1-LCR1 treatment, when all factors were at their low values.

Another important finding of the research was on the PHM. The PHM composite factor appeared as the statistically most significant predictor variable within the model. While four of the PHM sub-variables had statistically significant impact on the MOPs at all levels, the MFHBFA (Mean Flight Hours Between False Alarms) had a small statistically significant effect on the MOPs. Therefore, it may be concluded that the current level of the MFHBFA (which is 170 hours) is reasonably good for critical failures. The potential gains from the improvement of the MFHBFA are relatively smaller than the potential gains from other sub-variables.

Recommendations for Further Study

While building the simulation model, some important assumptions and limitations were defined. Investigating them offers potential to improve this research in many ways.

First, some parts of the model were developed using other aircraft's data due to the lack of real-world F-35 data. Future researches may attempt to obtain real F-35 data and update the associated parts of the model accordingly.

Second, this research only investigated mission critical failures and false positives within the sortie generation process. Additionally, the PHM system's prognostic capability was not modeled; since it was not functional at the time this research was conducted. Adding other failure types, false negatives and prognostic capability into the model may help it to produce more realistic outputs.

Third, analyzing the supply activities was beyond the scope of this study. However, the supply process is as important as maintenance in generating sorties. Moreover, the AL system aims to change and improve the supply activities considerably. Therefore, analyzing the sortie generation process from a supply standpoint may provide benefits for the decision makers in the supply area.

Fourth, all resources were assumed to have infinite capacity in the model. Therefore, queuing did not occur and so queuing effects on the sortie generation process were not analyzed. Adding equipment and human resources into the model and investigating the impacts of the resource levels on the MOPs may produce beneficial outputs for the decision makers in the equipment and personnel management areas.

Next, reliability growth and learning curves were two important phenomena embedded into the model logic. While the reliability growth rate was calculated based on actual F-35 data, the learning curve rate was defined as an assumption. Future researchers may focus on these concepts more deeply and update the model according to actual data when available.

Finally, while conducting this study, the researcher was not able to visit F-35 bases and review the overall sortie generation process in the field. Also, accessing F-35 field experts was problematic. Making field visits and interviewing with logistics personnel would make great contributions to the research. In particular, the modelling part could be more closely aligned to actual operations. We strongly recommend future researchers to make field visits to the F-35 bases, before building the simulation model.

Appendix A: Normality Test Results

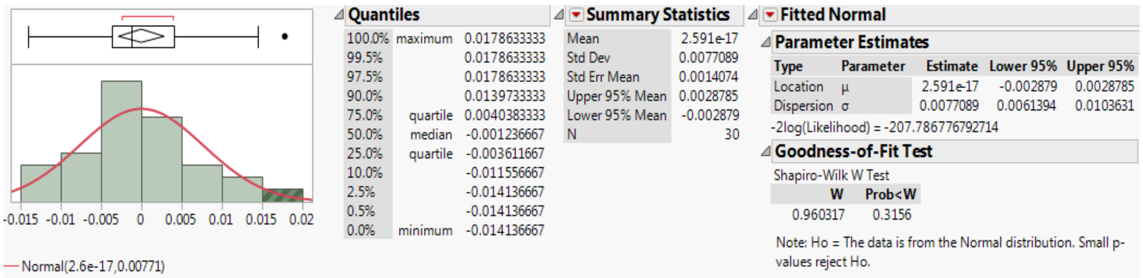


Figure 30. Shapiro-Wilk Test Results for the Residuals of FSE Rate

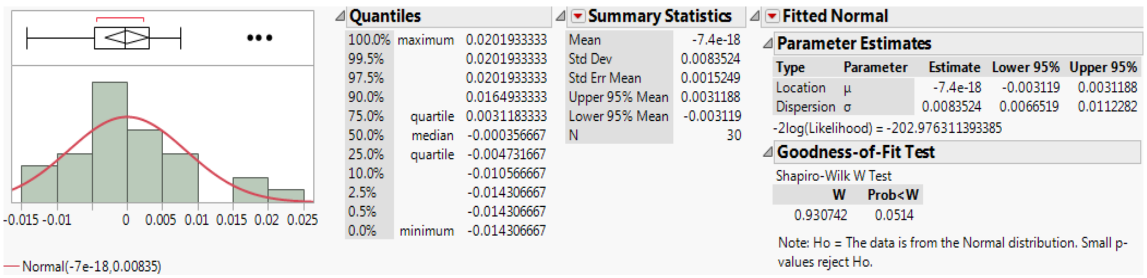


Figure 31. Shapiro-Wilk Test Results for the Residuals of AA Rate

Appendix B: Tests of the ANOVA Assumptions

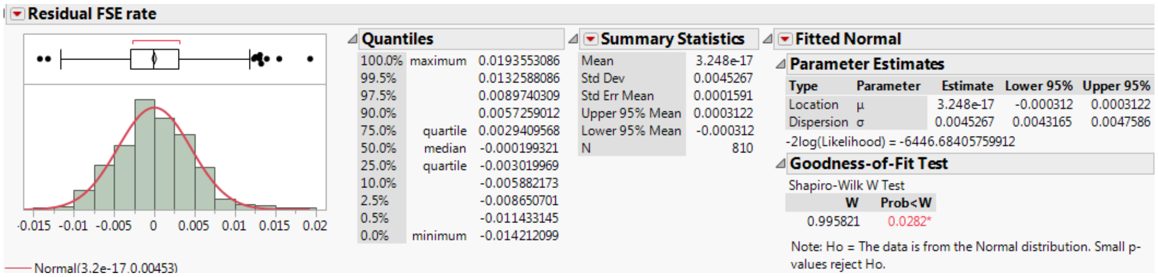


Figure 32. Shapiro-Wilk Test Results for FSE Rate (Normality)

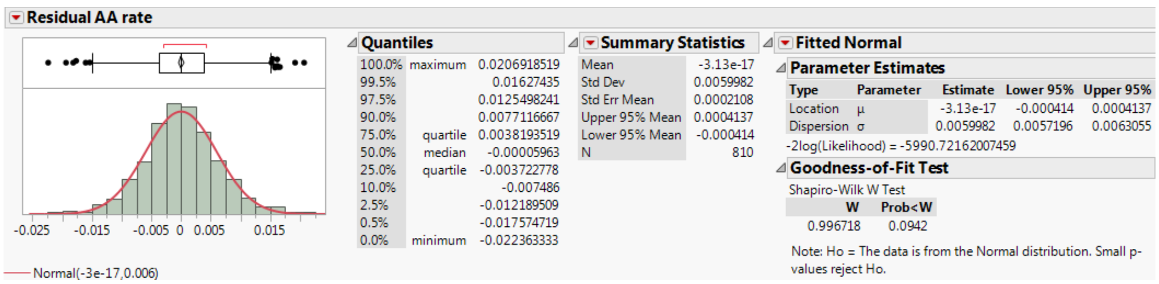


Figure 33. Shapiro-Wilk Test Results for AA rate (Normality)

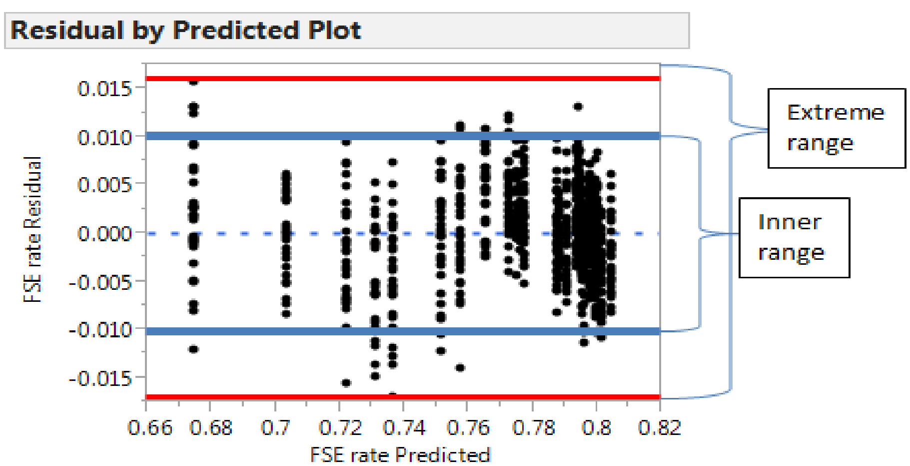


Figure 34. Residual Plot of the FSE Rate (Constant Variance)

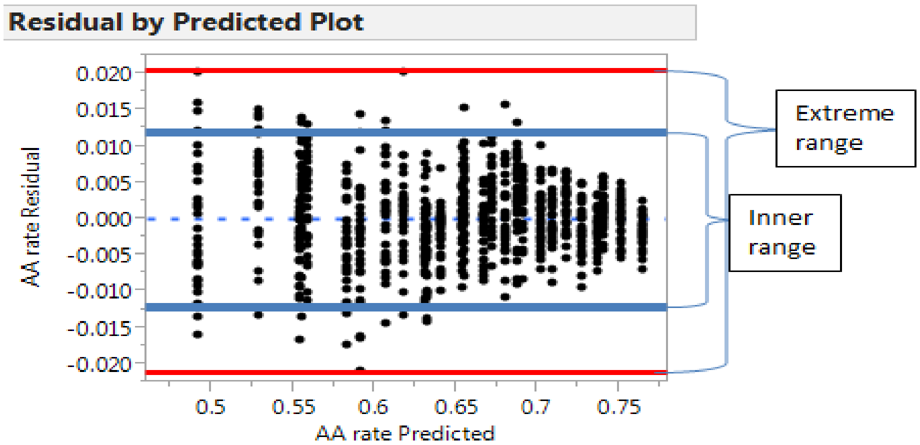


Figure 35. Residual Plot of the AA Rate (Constant Variance)

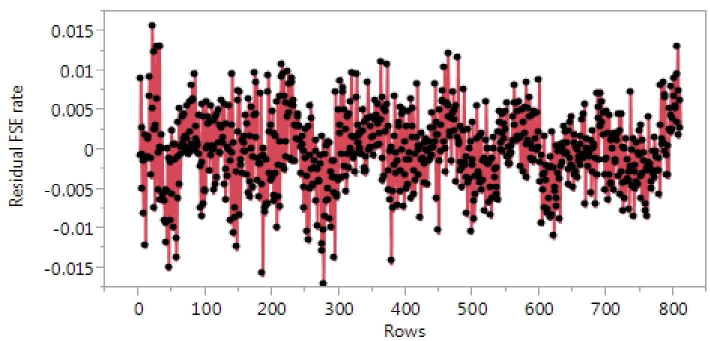


Figure 36. Overlay Plot of the FSE Rate's Residuals (Independence)

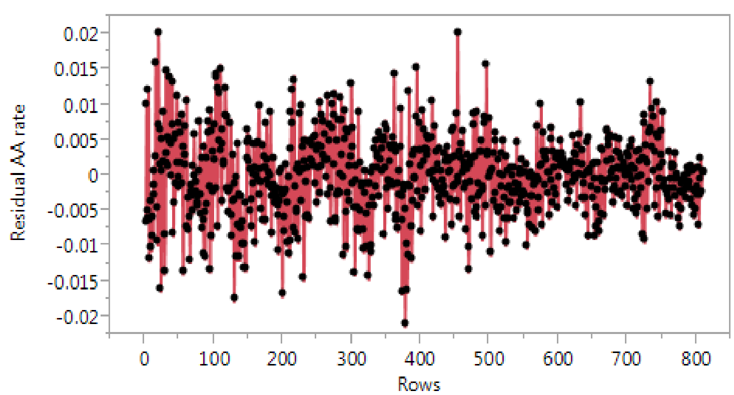


Figure 37. Overlay Plot of the AA Rate's Residuals (Independence)

Appendix C: Tukey Test Results for AA Rate

Table 23. Tukey Tests for PHM Level, RG Rate, and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	PHM1	PHM2	PHM3
PHM1	Mean[i]-Mean[j]	0	-0.0635	-0.1211
	Std Err Dif	0	0.00052	0.00052
	Lower CL Dif	0	-0.0647	-0.1224
	Upper CL Dif	0	-0.0622	-0.1199
PHM2	Mean[i]-Mean[j]	0.06347	0	-0.0577
	Std Err Dif	0.00052	0	0.00052
	Lower CL Dif	0.06224	0	-0.0589
	Upper CL Dif	0.06469	0	-0.0564
PHM3	Mean[i]-Mean[j]	0.12113	0.05766	0
	Std Err Dif	0.00052	0.00052	0
	Lower CL Dif	0.11991	0.05644	0
	Upper CL Dif	0.12236	0.05889	0

Level				Least Sq Mean
PHM3	A			0.71348037
PHM2		B		0.65581704
PHM1			C	0.59234815

Levels not connected by same letter are significantly different.

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	RGR1	RGR2	RGR3
RGR1	Mean[i]-Mean[j]	0	-0.0229	-0.0433
	Std Err Dif	0	0.00052	0.00052
	Lower CL Dif	0	-0.0241	-0.0446
	Upper CL Dif	0	-0.0216	-0.0421
RGR2	Mean[i]-Mean[j]	0.02286	0	-0.0205
	Std Err Dif	0.00052	0	0.00052
	Lower CL Dif	0.02164	0	-0.0217
	Upper CL Dif	0.02409	0	-0.0192
RGR3	Mean[i]-Mean[j]	0.04334	0.02047	0
	Std Err Dif	0.00052	0.00052	0
	Lower CL Dif	0.04211	0.01925	0
	Upper CL Dif	0.04456	0.0217	0

Level				Least Sq Mean
RGR3	A			0.67515185
RGR2		B		0.65467926
RGR1			C	0.63181444

Levels not connected by same letter are significantly different.

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	LCR1	LCR2	LCR3
LCR1	Mean[i]-Mean[j]	0	-0.0578	-0.108
	Std Err Dif	0	0.00052	0.00052
	Lower CL Dif	0	-0.059	-0.1092
	Upper CL Dif	0	-0.0566	-0.1068
LCR2	Mean[i]-Mean[j]	0.05781	0	-0.0502
	Std Err Dif	0.00052	0	0.00052
	Lower CL Dif	0.05658	0	-0.0514
	Upper CL Dif	0.05904	0	-0.049
LCR3	Mean[i]-Mean[j]	0.10802	0.05021	0
	Std Err Dif	0.00052	0.00052	0
	Lower CL Dif	0.10679	0.04898	0
	Upper CL Dif	0.10924	0.05143	0

Level				Least Sq Mean
LCR3	A			0.70662296
LCR2		B		0.65641630
LCR1			C	0.59860630

Levels not connected by same letter are signific

Table 24. Tukey Test for Two-way Interactions of PHM Level and RG Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	PHM1,R GR1	PHM1,R GR2	PHM1,R GR3	PHM2,R GR1	PHM2,R GR2	PHM2,R GR3	PHM3,R GR1	PHM3,R GR2	PHM3,R GR3
PHM1,RGR1	Mean[i]-Mean[j]	0	-0.0272	-0.0514	-0.0678	-0.0897	-0.1115	-0.1292	-0.1487	-0.1641
	Std Err Dif	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0	-0.03	-0.0542	-0.0706	-0.0925	-0.1143	-0.132	-0.1515	-0.1669
	Upper CL Dif	0	-0.0244	-0.0486	-0.0649	-0.0869	-0.1087	-0.1264	-0.1459	-0.1613
PHM1,RGR2	Mean[i]-Mean[j]	0.02718	0	-0.0242	-0.0406	-0.0626	-0.0843	-0.102	-0.1215	-0.1369
	Std Err Dif	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.02436	0	-0.027	-0.0434	-0.0654	-0.0871	-0.1048	-0.1243	-0.1397
	Upper CL Dif	0.02999	0	-0.0214	-0.0378	-0.0597	-0.0815	-0.0992	-0.1187	-0.1341
PHM1,RGR3	Mean[i]-Mean[j]	0.0514	0.02422	0	-0.0164	-0.0383	-0.0601	-0.0778	-0.0973	-0.1127
	Std Err Dif	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.04859	0.02141	0	-0.0192	-0.0411	-0.0629	-0.0806	-0.1001	-0.1155
	Upper CL Dif	0.05421	0.02704	0	-0.0135	-0.0355	-0.0573	-0.075	-0.0945	-0.1099
PHM2,RGR1	Mean[i]-Mean[j]	0.06776	0.04059	0.01636	0	-0.022	-0.0437	-0.0615	-0.0809	-0.0963
	Std Err Dif	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.06495	0.03777	0.01355	0	-0.0248	-0.0465	-0.0643	-0.0837	-0.0991
	Upper CL Dif	0.07057	0.0434	0.01917	0	-0.0192	-0.0409	-0.0586	-0.0781	-0.0935
PHM2,RGR2	Mean[i]-Mean[j]	0.08973	0.06255	0.03833	0.02197	0	-0.0218	-0.0395	-0.0589	-0.0744
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.08692	0.05974	0.03552	0.01915	0	-0.0246	-0.0423	-0.0617	-0.0772
	Upper CL Dif	0.09254	0.06536	0.04114	0.02478	0	-0.019	-0.0367	-0.0561	-0.0716
PHM2,RGR3	Mean[i]-Mean[j]	0.11149	0.08432	0.06009	0.04373	0.02176	0	-0.0177	-0.0372	-0.0526
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009
	Lower CL Dif	0.10868	0.0815	0.05728	0.04092	0.01895	0	-0.0205	-0.04	-0.0554
	Upper CL Dif	0.1143	0.08713	0.06291	0.04654	0.02458	0	-0.0149	-0.0344	-0.0498
PHM3,RGR1	Mean[i]-Mean[j]	0.12921	0.10204	0.07781	0.06145	0.03948	0.01772	0	-0.0195	-0.0349
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009
	Lower CL Dif	0.1264	0.09922	0.075	0.05864	0.03667	0.01491	0	-0.0223	-0.0377
	Upper CL Dif	0.13202	0.10485	0.08063	0.06426	0.0423	0.02053	0	-0.0166	-0.0321
PHM3,RGR2	Mean[i]-Mean[j]	0.14866	0.12149	0.09727	0.0809	0.05894	0.03717	0.01945	0	-0.0154
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009
	Lower CL Dif	0.14585	0.11868	0.09445	0.07809	0.05612	0.03436	0.01664	0	-0.0182
	Upper CL Dif	0.15148	0.1243	0.10008	0.08372	0.06175	0.03998	0.02226	0	-0.0126
PHM3,RGR3	Mean[i]-Mean[j]	0.16409	0.13692	0.1127	0.09633	0.07437	0.0526	0.03488	0.01543	0
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0
	Lower CL Dif	0.16128	0.13411	0.10988	0.09352	0.07155	0.04979	0.03207	0.01262	0
	Upper CL Dif	0.16691	0.13973	0.11551	0.09915	0.07718	0.05541	0.03769	0.01824	0

Level		Least Sq Mean
PHM3,RGR3	A	0.73025111
PHM3,RGR2	B	0.71482111
PHM3,RGR1	C	0.69536889
PHM2,RGR3	D	0.67764889
PHM2,RGR2	E	0.65588444
PHM2,RGR1	F	0.63391778
PHM1,RGR3	G	0.61755556
PHM1,RGR2	H	0.59333222
PHM1,RGR1	I	0.56615667

Levels not connected by same letter are significantly different.

Table 25. Tukey Test for Two-way Interactions of PHM Level and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	PHM1,LCR1	PHM1,LCR2	PHM1,LCR3	PHM2,LCR1	PHM2,LCR2	PHM2,LCR3	PHM3,LCR1	PHM3,LCR2	PHM3,LCR3
PHM1,LCR1		0	-0.0592	-0.1235	-0.0661	-0.1275	-0.1795	-0.1353	-0.1882	-0.2226
		0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
		0	-0.062	-0.1263	-0.0689	-0.1303	-0.1823	-0.1381	-0.191	-0.2254
		0	-0.0564	-0.1206	-0.0633	-0.1246	-0.1767	-0.1325	-0.1854	-0.2197
PHM1,LCR2		0.05921	0	-0.0642	-0.0069	-0.0682	-0.1203	-0.0761	-0.129	-0.1633
		0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
		0.0564	0	-0.0671	-0.0097	-0.0711	-0.1231	-0.0789	-0.1318	-0.1662
		0.06202	0	-0.0614	-0.0041	-0.0654	-0.1175	-0.0733	-0.1262	-0.1605
PHM1,LCR3		0.12346	0.06425	0	0.05733	-0.004	-0.056	-0.0119	-0.0647	-0.0991
		0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
		0.12064	0.06143	0	0.05452	-0.0068	-0.0588	-0.0147	-0.0676	-0.1019
		0.12627	0.06706	0	0.06014	-0.0012	-0.0532	-0.009	-0.0619	-0.0963
PHM2,LCR1		0.06613	0.00692	-0.0573	0	-0.0613	-0.1134	-0.0692	-0.1221	-0.1564
		0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009
		0.06332	0.00411	-0.0601	0	-0.0641	-0.1162	-0.072	-0.1249	-0.1592
		0.06894	0.00973	-0.0545	0	-0.0585	-0.1105	-0.0664	-0.1193	-0.1536
PHM2,LCR2		0.12746	0.06825	0.004	0.06133	0	-0.052	-0.0079	-0.0607	-0.0951
		0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009
		0.12465	0.06544	0.00119	0.05852	0	-0.0548	-0.0107	-0.0636	-0.0979
		0.13027	0.07106	0.00682	0.06414	0	-0.0492	-0.005	-0.0579	-0.0923
PHM2,LCR3		0.17948	0.12027	0.05603	0.11336	0.05202	0	0.04417	-0.0087	-0.0431
		0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009
		0.17667	0.11746	0.05322	0.11054	0.04921	0	0.04136	-0.0115	-0.0459
		0.1823	0.12309	0.05884	0.11617	0.05484	0	0.04698	-0.0059	-0.0403
PHM3,LCR1		0.13531	0.0761	0.01186	0.06918	0.00785	-0.0442	0	-0.0529	-0.0872
		0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009
		0.1325	0.07329	0.00904	0.06637	0.00504	-0.047	0	-0.0557	-0.0901
		0.13813	0.07891	0.01467	0.072	0.01066	-0.0414	0	-0.0501	-0.0844
PHM3,LCR2		0.1882	0.12899	0.06474	0.12207	0.06074	0.00872	0.05289	0	-0.0344
		0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009
		0.18539	0.12618	0.06193	0.11926	0.05793	0.0059	0.05007	0	-0.0372
		0.19101	0.1318	0.06756	0.12488	0.06355	0.01153	0.0557	0	-0.0315
PHM3,LCR3		0.22255	0.16334	0.09909	0.15642	0.09509	0.04307	0.08724	0.03435	0
		0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0
		0.21974	0.16053	0.09628	0.15361	0.09228	0.04025	0.08443	0.03154	0
		0.22536	0.16615	0.10191	0.15923	0.0979	0.04588	0.09005	0.03716	0

Level										Least Sq Mean
PHM3,LCR3	A									0.75401000
PHM3,LCR2		B								0.71965889
PHM2,LCR3			C							0.71094333
PHM3,LCR1				D						0.66677222
PHM2,LCR2					E					0.65892000
PHM1,LCR3						F				0.65491556
PHM2,LCR1							G			0.59758778
PHM1,LCR2								H		0.59067000
PHM1,LCR1									I	0.53145889

Levels not connected by same letter are significantly different.

Table 26. Tukey Test for Two-way Interactions of RG Rate and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	RGR1,LCR1	RGR1,LCR2	RGR1,LCR3	RGR2,LCR1	RGR2,LCR2	RGR2,LCR3	RGR3,LCR1	RGR3,LCR2	RGR3,LCR3
RGR1,LCR1	Mean[i]-Mean[j]	0	-0.0662	-0.1183	-0.0295	-0.0856	-0.1379	-0.0553	-0.1065	-0.1526
	Std Err Dif	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0	-0.069	-0.1211	-0.0324	-0.0884	-0.1408	-0.0581	-0.1093	-0.1555
	Upper CL Dif	0	-0.0633	-0.1155	-0.0267	-0.0828	-0.1351	-0.0525	-0.1037	-0.1498
RGR1,LCR2	Mean[i]-Mean[j]	0.06616	0	-0.0521	0.03662	-0.0194	-0.0718	0.01087	-0.0404	-0.0865
	Std Err Dif	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.06335	0	-0.0549	0.03381	-0.0222	-0.0746	0.00806	-0.0432	-0.0893
	Upper CL Dif	0.06897	0	-0.0493	0.03943	-0.0166	-0.069	0.01368	-0.0376	-0.0837
RGR1,LCR3	Mean[i]-Mean[j]	0.11829	0.05213	0	0.08875	0.03273	-0.0197	0.063	0.01176	-0.0344
	Std Err Dif	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.11548	0.04932	0	0.08594	0.02991	-0.0225	0.06019	0.00895	-0.0372
	Upper CL Dif	0.1211	0.05494	0	0.09157	0.03554	-0.0168	0.06581	0.01457	-0.0315
RGR2,LCR1	Mean[i]-Mean[j]	0.02954	-0.0366	-0.0888	0	-0.056	-0.1084	-0.0258	-0.077	-0.1231
	Std Err Dif	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.02673	-0.0394	-0.0916	0	-0.0588	-0.1112	-0.0286	-0.0798	-0.1259
	Upper CL Dif	0.03235	-0.0338	-0.0859	0	-0.0532	-0.1056	-0.0229	-0.0742	-0.1203
RGR2,LCR2	Mean[i]-Mean[j]	0.08557	0.0194	-0.0327	0.05603	0	-0.0524	0.03028	-0.021	-0.0671
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009	0.0009
	Lower CL Dif	0.08275	0.01659	-0.0355	0.05321	0	-0.0552	0.02746	-0.0238	-0.0699
	Upper CL Dif	0.08838	0.02222	-0.0299	0.05884	0	-0.0496	0.03309	-0.0182	-0.0643
RGR2,LCR3	Mean[i]-Mean[j]	0.13794	0.07178	0.01965	0.1084	0.05238	0	0.08265	0.03141	-0.0147
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009	0.0009
	Lower CL Dif	0.13513	0.06897	0.01684	0.10559	0.04957	0	0.07984	0.0286	-0.0175
	Upper CL Dif	0.14076	0.07459	0.02246	0.11122	0.05519	0	0.08547	0.03422	-0.0119
RGR3,LCR1	Mean[i]-Mean[j]	0.05529	-0.0109	-0.063	0.02575	-0.0303	-0.0827	0	-0.0512	-0.0974
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009	0.0009
	Lower CL Dif	0.05248	-0.0137	-0.0658	0.02294	-0.0331	-0.0855	0	-0.0541	-0.1002
	Upper CL Dif	0.0581	-0.0081	-0.0602	0.02856	-0.0275	-0.0798	0	-0.0484	-0.0945
RGR3,LCR2	Mean[i]-Mean[j]	0.10653	0.04037	-0.0118	0.07699	0.02097	-0.0314	0.05124	0	-0.0461
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0	0.0009
	Lower CL Dif	0.10372	0.03756	-0.0146	0.07418	0.01815	-0.0342	0.04843	0	-0.0489
	Upper CL Dif	0.10934	0.04318	-0.0089	0.07981	0.02378	-0.0286	0.05405	0	-0.0433
RGR3,LCR3	Mean[i]-Mean[j]	0.15264	0.08648	0.03435	0.1231	0.06708	0.0147	0.09735	0.04611	0
	Std Err Dif	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0
	Lower CL Dif	0.14983	0.08367	0.03154	0.12029	0.06427	0.01189	0.09454	0.0433	0
	Upper CL Dif	0.15546	0.08929	0.03716	0.12592	0.06989	0.01751	0.10017	0.04892	0

Level		Least Sq Mean
RGR3,LCR3	A	0.72297333
RGR2,LCR3	B	0.70827333
RGR1,LCR3	C	0.68862222
RGR3,LCR2	D	0.67686222
RGR2,LCR2	E	0.65589556
RGR1,LCR2	F	0.63649111
RGR3,LCR1	G	0.62562000
RGR2,LCR1	H	0.59986889
RGR1,LCR1	I	0.57033000

Levels not connected by same letter are significantly different.

Appendix D: Tukey Test Results for FSE Rate

Table 27. Tukey Tests for PHM Level, RG Rate, and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	PHM1	PHM2	PHM3
PHM1	Mean[i]-Mean[j]	0	-0.0345	-0.0467
	Std Err Dif	0	0.00039	0.00039
	Lower CL Dif	0	-0.0355	-0.0476
	Upper CL Dif	0	-0.0336	-0.0458
PHM2	Mean[i]-Mean[j]	0.03453	0	-0.0122
	Std Err Dif	0.00039	0	0.00039
	Lower CL Dif	0.0336	0	-0.0131
	Upper CL Dif	0.03545	0	-0.0112
PHM3	Mean[i]-Mean[j]	0.04669	0.01216	0
	Std Err Dif	0.00039	0.00039	0
	Lower CL Dif	0.04577	0.01124	0
	Upper CL Dif	0.04762	0.01309	0

Level				Least Sq Mean
PHM3	A			0.80681148
PHM2		B		0.79464889
PHM1			C	0.76012037

Levels not connected by same letter are significantly different.

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	RGR1	RGR2	RGR3
RGR1	Mean[i]-Mean[j]	0	-0.0118	-0.02
	Std Err Dif	0	0.00039	0.00039
	Lower CL Dif	0	-0.0128	-0.0209
	Upper CL Dif	0	-0.0109	-0.0191
RGR2	Mean[i]-Mean[j]	0.01184	0	-0.0082
	Std Err Dif	0.00039	0	0.00039
	Lower CL Dif	0.01092	0	-0.0091
	Upper CL Dif	0.01277	0	-0.0072
RGR3	Mean[i]-Mean[j]	0.02	0.00815	0
	Std Err Dif	0.00039	0.00039	0
	Lower CL Dif	0.01907	0.00723	0
	Upper CL Dif	0.02092	0.00908	0

Level				Least Sq Mean
RGR3	A			0.79657778
RGR2		B		0.78842296
RGR1			C	0.77658000

Levels not connected by same letter are significantly different.

LSMeans Differences Tukey HSD

α= 0.050 Q= 2.34813

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	LCR1	LCR2	LCR3
LCR1	Mean[i]-Mean[j]	0	-0.0299	-0.0452
	Std Err Dif	0	0.00039	0.00039
	Lower CL Dif	0	-0.0308	-0.0461
	Upper CL Dif	0	-0.029	-0.0443
LCR2	Mean[i]-Mean[j]	0.02988	0	-0.0153
	Std Err Dif	0.00039	0	0.00039
	Lower CL Dif	0.02895	0	-0.0163
	Upper CL Dif	0.0308	0	-0.0144
LCR3	Mean[i]-Mean[j]	0.04522	0.01534	0
	Std Err Dif	0.00039	0.00039	0
	Lower CL Dif	0.04429	0.01442	0
	Upper CL Dif	0.04614	0.01627	0

Level				Least Sq Mean
LCR3	A			0.80738148
LCR2		B		0.79203741
LCR1			C	0.76216185

Levels not connected by same letter are signific

Table 28. Tukey Test for Two-way Interactions of PHM Level and RG Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	PHM1,RGR1	PHM1,RGR2	PHM1,RGR3	PHM2,RGR1	PHM2,RGR2	PHM2,RGR3	PHM3,RGR1	PHM3,RGR2	PHM3,RGR3
PHM1,RGR1	Mean[i]-Mean[j]	0	-0.02	-0.0332	-0.0417	-0.0532	-0.0618	-0.0609	-0.0649	-0.0675
	Std Err Dif	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0	-0.0221	-0.0353	-0.0438	-0.0554	-0.064	-0.063	-0.067	-0.0696
	Upper CL Dif	0	-0.0178	-0.0311	-0.0395	-0.0511	-0.0597	-0.0587	-0.0627	-0.0654
PHM1,RGR2	Mean[i]-Mean[j]	0.01995	0	-0.0132	-0.0217	-0.0333	-0.0419	-0.0409	-0.0449	-0.0475
	Std Err Dif	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.01783	0	-0.0154	-0.0238	-0.0354	-0.044	-0.043	-0.047	-0.0497
	Upper CL Dif	0.02207	0	-0.0111	-0.0196	-0.0312	-0.0398	-0.0388	-0.0428	-0.0454
PHM1,RGR3	Mean[i]-Mean[j]	0.0332	0.01325	0	-0.0085	-0.02	-0.0286	-0.0277	-0.0317	-0.0343
	Std Err Dif	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.03107	0.01112	0	-0.0106	-0.0222	-0.0308	-0.0298	-0.0338	-0.0364
	Upper CL Dif	0.03532	0.01537	0	-0.0063	-0.0179	-0.0265	-0.0256	-0.0295	-0.0322
PHM2,RGR1	Mean[i]-Mean[j]	0.04165	0.0217	0.00846	0	-0.0116	-0.0202	-0.0192	-0.0232	-0.0258
	Std Err Dif	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.03953	0.01958	0.00634	0	-0.0137	-0.0223	-0.0213	-0.0253	-0.028
	Upper CL Dif	0.04378	0.02383	0.01058	0	-0.0095	-0.0181	-0.0171	-0.0211	-0.0237
PHM2,RGR2	Mean[i]-Mean[j]	0.05324	0.03329	0.02005	0.01159	0	-0.0086	-0.0076	-0.0116	-0.0142
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.05112	0.03117	0.01793	0.00947	0	-0.0107	-0.0098	-0.0137	-0.0164
	Upper CL Dif	0.05537	0.03542	0.02217	0.01371	0	-0.0065	-0.0055	-0.0095	-0.0121
PHM2,RGR3	Mean[i]-Mean[j]	0.06183	0.04188	0.02864	0.02018	0.00859	0	0.00096	-0.003	-0.0057
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068
	Lower CL Dif	0.05971	0.03976	0.02652	0.01806	0.00647	0	-0.0012	-0.0051	-0.0078
	Upper CL Dif	0.06396	0.04401	0.03076	0.0223	0.01071	0	0.00308	-0.0009	-0.0035
PHM3,RGR1	Mean[i]-Mean[j]	0.06087	0.04092	0.02768	0.01922	0.00763	-0.001	0	-0.004	-0.0066
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068
	Lower CL Dif	0.05875	0.0388	0.02555	0.0171	0.00551	-0.0031	0	-0.0061	-0.0087
	Upper CL Dif	0.06299	0.04304	0.0298	0.02134	0.00975	0.00116	0	-0.0019	-0.0045
PHM3,RGR2	Mean[i]-Mean[j]	0.06486	0.04491	0.03166	0.02321	0.01162	0.00303	0.00399	0	-0.0026
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068
	Lower CL Dif	0.06274	0.04279	0.02954	0.02108	0.00949	0.0009	0.00187	0	-0.0048
	Upper CL Dif	0.06698	0.04703	0.03379	0.02533	0.01374	0.00515	0.00611	0	-0.0005
PHM3,RGR3	Mean[i]-Mean[j]	0.06749	0.04754	0.03429	0.02583	0.01424	0.00565	0.00662	0.00263	0
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0
	Lower CL Dif	0.06537	0.04542	0.03217	0.02371	0.01212	0.00353	0.00449	0.00051	0
	Upper CL Dif	0.06961	0.04966	0.03641	0.02796	0.01637	0.00778	0.00874	0.00475	0

Level									Least Sq Mean
PHM3,RGR3	A								0.80989333
PHM3,RGR2		B							0.80726444
PHM2,RGR3			C						0.80423889
PHM3,RGR1			C						0.80327667
PHM2,RGR2				D					0.79564889
PHM2,RGR1					E				0.78405889
PHM1,RGR3						F			0.77560111
PHM1,RGR2							G		0.76235556
PHM1,RGR1								H	0.74240444

Levels not connected by same letter are significantly different.

Table 29. Tukey Test for Two-way Interactions of PHM Level and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	PHM1,LCR1	PHM1,LCR2	PHM1,LCR3	PHM2,LCR1	PHM2,LCR2	PHM2,LCR3	PHM3,LCR1	PHM3,LCR2	PHM3,LCR3
PHM1,LCR1	Mean[i]-Mean[j]	0	-0.0461	-0.0812	-0.0519	-0.0842	-0.0948	-0.0815	-0.0927	-0.0931
	Std Err Dif	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0	-0.0482	-0.0833	-0.054	-0.0863	-0.0969	-0.0837	-0.0948	-0.0952
	Upper CL Dif	0	-0.044	-0.0791	-0.0498	-0.0821	-0.0927	-0.0794	-0.0906	-0.091
PHM1,LCR2	Mean[i]-Mean[j]	0.04612	0	-0.0351	-0.0058	-0.0381	-0.0487	-0.0354	-0.0466	-0.047
	Std Err Dif	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.044	0	-0.0372	-0.0079	-0.0402	-0.0508	-0.0375	-0.0487	-0.0491
	Upper CL Dif	0.04824	0	-0.0329	-0.0036	-0.036	-0.0466	-0.0333	-0.0445	-0.0449
PHM1,LCR3	Mean[i]-Mean[j]	0.08118	0.03506	0	0.0293	-0.003	-0.0136	-0.0004	-0.0115	-0.0119
	Std Err Dif	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.07905	0.03293	0	0.02718	-0.0052	-0.0157	-0.0025	-0.0137	-0.0141
	Upper CL Dif	0.0833	0.03718	0	0.03142	-0.0009	-0.0115	0.00175	-0.0094	-0.0098
PHM2,LCR1	Mean[i]-Mean[j]	0.05187	0.00576	-0.0293	0	-0.0323	-0.0429	-0.0297	-0.0408	-0.0412
	Std Err Dif	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.04975	0.00363	-0.0314	0	-0.0345	-0.045	-0.0318	-0.043	-0.0434
	Upper CL Dif	0.054	0.00788	-0.0272	0	-0.0302	-0.0408	-0.0275	-0.0387	-0.0391
PHM2,LCR2	Mean[i]-Mean[j]	0.08421	0.03809	0.00304	0.03234	0	-0.0106	0.00267	-0.0085	-0.0089
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.08209	0.03597	0.00091	0.03022	0	-0.0127	0.00055	-0.0106	-0.011
	Upper CL Dif	0.08633	0.04022	0.00516	0.03446	0	-0.0085	0.00479	-0.0064	-0.0068
PHM2,LCR3	Mean[i]-Mean[j]	0.09479	0.04867	0.01362	0.04292	0.01058	0	0.01325	0.00208	0.00168
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068
	Lower CL Dif	0.09267	0.04655	0.0115	0.0408	0.00846	0	0.01113	-4.4e-5	-0.0004
	Upper CL Dif	0.09692	0.0508	0.01574	0.04504	0.0127	0	0.01537	0.0042	0.00381
PHM3,LCR1	Mean[i]-Mean[j]	0.08154	0.03543	0.00037	0.02967	-0.0027	-0.0132	0	-0.0112	-0.0116
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068
	Lower CL Dif	0.07942	0.0333	-0.0018	0.02755	-0.0048	-0.0154	0	-0.0133	-0.0137
	Upper CL Dif	0.08367	0.03755	0.00249	0.03179	-0.0005	-0.0111	0	-0.009	-0.0094
PHM3,LCR2	Mean[i]-Mean[j]	0.09271	0.0466	0.01154	0.04084	0.0085	-0.0021	0.01117	0	-0.0004
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068
	Lower CL Dif	0.09059	0.04447	0.00942	0.03872	0.00638	-0.0042	0.00905	0	-0.0025
	Upper CL Dif	0.09484	0.04872	0.01366	0.04296	0.01062	4.38e-5	0.01329	0	0.00173
PHM3,LCR3	Mean[i]-Mean[j]	0.09311	0.04699	0.01193	0.04123	0.0089	-0.0017	0.01156	0.00039	0
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0
	Lower CL Dif	0.09099	0.04487	0.00981	0.03911	0.00677	-0.0038	0.00944	-0.0017	0
	Upper CL Dif	0.09523	0.04911	0.01406	0.04336	0.01102	0.00044	0.01369	0.00252	0

Level							Least Sq Mean
PHM2,LCR3	A						0.81248222
PHM3,LCR3	A						0.81079778
PHM3,LCR2	A						0.81040333
PHM2,LCR2		B					0.80190111
PHM3,LCR1			C				0.79923333
PHM1,LCR3			C				0.79886444
PHM2,LCR1				D			0.76956333
PHM1,LCR2					E		0.76380778
PHM1,LCR1						F	0.71768889

Levels not connected by same letter are significantly different.

Table 30. Tukey Test for Two-way Interactions of RG Rate and LC Rate

LSMeans Differences Tukey HSD

α= 0.050 Q= 3.11039

LSMean[j]

LSMean[i]	Mean[i]-Mean[j] / Std Err Dif / Lower CL Dif / Upper CL Dif	RGR1,LCR1	RGR1,LCR2	RGR1,LCR3	RGR2,LCR1	RGR2,LCR2	RGR2,LCR3	RGR3,LCR1	RGR3,LCR2	RGR3,LCR3
RGR1,LCR1	Mean[i]-Mean[j]	0	-0.0381	-0.0589	-0.0204	-0.0484	-0.0638	-0.0334	-0.0569	-0.0668
	Std Err Dif	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0	-0.0403	-0.0611	-0.0225	-0.0505	-0.0659	-0.0355	-0.059	-0.0689
	Upper CL Dif	0	-0.036	-0.0568	-0.0183	-0.0463	-0.0617	-0.0313	-0.0548	-0.0646
RGR1,LCR2	Mean[i]-Mean[j]	0.03814	0	-0.0208	0.01772	-0.0103	-0.0256	0.00474	-0.0188	-0.0286
	Std Err Dif	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.03602	0	-0.0229	0.0156	-0.0124	-0.0278	0.00261	-0.0209	-0.0308
	Upper CL Dif	0.04026	0	-0.0187	0.01984	-0.0081	-0.0235	0.00686	-0.0166	-0.0265
RGR1,LCR3	Mean[i]-Mean[j]	0.05894	0.0208	0	0.03852	0.01053	-0.0048	0.02553	0.00204	-0.0078
	Std Err Dif	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.05682	0.01867	0	0.0364	0.0084	-0.007	0.02341	-0.0001	-0.01
	Upper CL Dif	0.06106	0.02292	0	0.04064	0.01265	-0.0027	0.02765	0.00416	-0.0057
RGR2,LCR1	Mean[i]-Mean[j]	0.02042	-0.0177	-0.0385	0	-0.028	-0.0434	-0.013	-0.0365	-0.0464
	Std Err Dif	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.0183	-0.0198	-0.0406	0	-0.0301	-0.0455	-0.0151	-0.0386	-0.0485
	Upper CL Dif	0.02254	-0.0156	-0.0364	0	-0.0259	-0.0412	-0.0109	-0.0344	-0.0442
RGR2,LCR2	Mean[i]-Mean[j]	0.04841	0.01027	-0.0105	0.02799	0	-0.0154	0.01501	-0.0085	-0.0184
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068	0.00068
	Lower CL Dif	0.04629	0.00815	-0.0126	0.02587	0	-0.0175	0.01288	-0.0106	-0.0205
	Upper CL Dif	0.05053	0.01239	-0.0084	0.03011	0	-0.0132	0.01713	-0.0064	-0.0162
RGR2,LCR3	Mean[i]-Mean[j]	0.06378	0.02563	0.00484	0.04336	0.01536	0	0.03037	0.00688	-0.003
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068	0.00068
	Lower CL Dif	0.06165	0.02351	0.00272	0.04123	0.01324	0	0.02825	0.00476	-0.0051
	Upper CL Dif	0.0659	0.02776	0.00696	0.04548	0.01749	0	0.03249	0.009	-0.0009
RGR3,LCR1	Mean[i]-Mean[j]	0.03341	-0.0047	-0.0255	0.01299	-0.015	-0.0304	0	-0.0235	-0.0334
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068	0.00068
	Lower CL Dif	0.03128	-0.0069	-0.0277	0.01086	-0.0171	-0.0325	0	-0.0256	-0.0355
	Upper CL Dif	0.03553	-0.0026	-0.0234	0.01511	-0.0129	-0.0282	0	-0.0214	-0.0312
RGR3,LCR2	Mean[i]-Mean[j]	0.0569	0.01876	-0.002	0.03648	0.00849	-0.0069	0.02349	0	-0.0099
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0	0.00068
	Lower CL Dif	0.05478	0.01663	-0.0042	0.03436	0.00636	-0.009	0.02137	0	-0.012
	Upper CL Dif	0.05902	0.02088	8.27e-5	0.0386	0.01061	-0.0048	0.02561	0	-0.0077
RGR3,LCR3	Mean[i]-Mean[j]	0.06677	0.02863	0.00783	0.04635	0.01836	0.00299	0.03336	0.00987	0
	Std Err Dif	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0.00068	0
	Lower CL Dif	0.06465	0.02651	0.00571	0.04423	0.01624	0.00087	0.03124	0.00775	0
	Upper CL Dif	0.06889	0.03075	0.00995	0.04847	0.02048	0.00512	0.03549	0.01199	0

Level		Least Sq Mean
RGR3,LCR3	A	0.81099000
RGR2,LCR3	B	0.80799667
RGR1,LCR3	C	0.80315778
RGR3,LCR2	C	0.80111778
RGR2,LCR2	D	0.79263222
RGR1,LCR2	E	0.78236222
RGR3,LCR1	F	0.77762556
RGR2,LCR1	G	0.76464000
RGR1,LCR1	H	0.74422000

Levels not connected by same letter are significantly different.

Appendix E: ANOVA Results for MFHBFA

Table 31. ANOVA of the MFHBFA vs. Maintenance Time

Summary of Fit

RSquare	0.108582
RSquare Adj	0.09797
Root Mean Square Error	787.2074
Mean of Response	83425.51
Observations (or Sum Wgts)	86

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	6340644	6340644	10.2319
Error	84	52054418	619695	**Prob > F**
C. Total	85	58395061		0.0019*

Table 32. ANOVA of the MFHBFA vs. AA Rate

Summary of Fit

RSquare	0.050155
RSquare Adj	0.038848
Root Mean Square Error	0.007363
Mean of Response	0.495758
Observations (or Sum Wgts)	86

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.00024048	0.000240	4.4355
Error	84	0.00455415	0.000054	**Prob > F**
C. Total	85	0.00479463		0.0382*

Table 33. ANOVA of the MFHBFA vs. FSE Rate

Summary of Fit

RSquare	0.069577
RSquare Adj	0.0585
Root Mean Square Error	0.005988
Mean of Response	0.69375
Observations (or Sum Wgts)	86

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.00022525	0.000225	6.2815
Error	84	0.00301219	0.000036	**Prob > F**
C. Total	85	0.00323743		0.0141*

Appendix F: ANOVA Results for FCR

Table 34. ANOVA of the FCR vs. FSE Rate

Summary of Fit

RSquare	0.6525
RSquare Adj	0.648551
Root Mean Square Error	0.00642
Mean of Response	0.703114
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.00680998	0.006810	165.2371
Error	88	0.00362678	0.000041	**Prob > F**
C. Total	89	0.01043675		<.0001*

Table 35. ANOVA of the FCR vs. AA Rate

Summary of Fit

RSquare	0.67558
RSquare Adj	0.671893
Root Mean Square Error	0.007981
Mean of Response	0.507963
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.01167293	0.011673	183.2529
Error	88	0.00560546	0.000064	**Prob > F**
C. Total	89	0.01727839		<.0001*

Appendix G: ANOVA Results for CFDR

Table 36. ANOVA of the CFDR vs. FSE Rate

Summary of Fit

RSquare	0.834445
RSquare Adj	0.832564
Root Mean Square Error	0.005443
Mean of Response	0.708038
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.01314240	0.013142	443.5451
Error	88	0.00260747	0.000030	**Prob > F**
C. Total	89	0.01574987		<.0001*

Table 37. ANOVA of the CFDR vs. AA Rate

Summary of Fit

RSquare	0.828092
RSquare Adj	0.826139
Root Mean Square Error	0.007798
Mean of Response	0.515607
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.02577568	0.025776	423.9031
Error	88	0.00535089	0.000061	**Prob > F**
C. Total	89	0.03112658		<.0001*

Appendix H: ANOVA Results for FIR

Table 38. ANOVA of the FIR vs. FSE Rate

Summary of Fit

RSquare	0.776166
RSquare Adj	0.773623
Root Mean Square Error	0.006142
Mean of Response	0.707297
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.01151292	0.011513	305.1493
Error	88	0.00332013	0.000038	Prob > F
C. Total	89	0.01483305		<.0001*

Table 39. ANOVA of the FIR vs. AA Rate

Summary of Fit

RSquare	0.766916
RSquare Adj	0.764268
Root Mean Square Error	0.008871
Mean of Response	0.514322
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.02278392	0.022784	289.5470
Error	88	0.00692456	0.000079	Prob > F
C. Total	89	0.02970848		<.0001*

Appendix I: ANOVA Results for KFAR

Table 40. ANOVA of the KFAR vs. FSE Rate

Summary of Fit

RSquare	0.962543
RSquare Adj	0.962117
Root Mean Square Error	0.005628
Mean of Response	0.728201
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.07161524	0.071615	2261.369
Error	88	0.00278687	0.000032	**Prob > F**
C. Total	89	0.07440211		<.0001*

Table 41. ANOVA of the KFAR vs. AA Rate

Summary of Fit

RSquare	0.938323
RSquare Adj	0.937622
Root Mean Square Error	0.009816
Mean of Response	0.545301
Observations (or Sum Wgts)	90

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.12899207	0.128992	1338.795
Error	88	0.00847874	0.000096	**Prob > F**
C. Total	89	0.13747081		<.0001*

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14. ABSTRACT
Parallel to the developments in diagnostic and prognostic technology, autonomic logistics systems (ALS) have been a potential improvement for the aircraft sortie generation process. Currently, Lockheed Martin and the Joint Program Office are developing a new autonomic logistics system for the multibillion F-35 Lightning Joint Strike Fighter project, which is named the ‘’Autonomic Logistics Information System (ALIS).’’
Generally, researchers make an analogy between the ALS and the human body's autonomic nervous system since both of them monitor, control, and adjust autonomic responses to external stimuli. Based on this perspective, ALS aims to switch the Air Force logistics mentality from a reactive one into a proactive one to achieve higher sortie generation rates and aircraft availability.
The primary objective of this thesis is to explore the ALS concept in detail and to investigate the F-35's sortie generation process through a discrete-event simulation model developed in Arena® Simulation Software.

15. SUBJECT TERMS
Sortie Generation, Discrete-event Simulation, Autonomic Logistics, Learning Curves, Reliability Growth

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